Paper:

# Development of Crane Vision for Positioning Container

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**Pattern recognition under the outdoor environment is very difficult in general because of the change in the brightness distribution of the object based on the change in the lighting condition. Combining distributed sensing with expanded template matching, the technique for achieving effective pattern recognition under the outdoor environment was developed. We applied it to the detection of a relative position of a spreader of a quayside gantry crane and the target container, made a prototype machine, and named Crane Vision. This paper details Crane Vision's measurement principle, system configuration, experimental results, and demonstrates the validity of pattern recognition under the outdoor environment.**

**Keywords:** pattern recognition, distributed sensing, template matching, outdoor environment, container

## 1. Introduction

Quayside gantry cranes are specialized for container handling on wharves of container terminals for loading and unloading cargo containers for container ships. Container handling is currently done by remote manual operation by an operator in the crane's cabin who relies on visual observation. Container handling efficiency thus depends more on operator skill rather than crane performance. The growing shortage of skilled operators necessitating the development of a crane that provides sufficient container handling performance that operator skill becomes less of a consideration.

We studied ways to improve crane container handling efficiency by developing automated container handling conventionally done by remote manual operation [1-3]. Advances in the technology for measuring the relative positioning of the spreader, an integral quayside crane component used for hoisting containers, and containers are particularly important.

Pattern recognition under the outdoor environment is very difficult in general because of the change in the brightness distribution of the object based on the change in the lighting condition. Combining distributed sensing with expanded template matching, the technique for achieving effective pattern recognition under the outdoor environment was developed. We applied it to the detection of a relative position of a spreader of a quayside gantry crane and the target container, made a prototype machine, and named Crane Vision.

This paper details Crane Vision's measurement principle, system configuration, and experimental results, and demonstrates the feasibility of this pattern recognition under the outdoor environment. Section 2 outlines container handling and operational issues in real environments. Section 3 describes crane vision measurement principles. Section 4 presents the system configuration. Section 5 discusses basic crane vision performance based on experimental results. Section 6 presents our conclusions and projected work.

## 2. Container Handling and Operational Issues in Real Environments

### 2.1. Container Handling

**Figure 1** shows a quayside gantry crane. **Fig.2** shows the equipment used for container handling. A quayside gantry crane lifts loads 30-40 m, has a span 20-30 m, and reaches 40-50 m. It is 8 ft (2.4 m) wide, 8-9 ft (2.4-2.7 m) high, and either 40 ft (12 m) or 20 ft (6 m) long.

Container handling involves inserting twist lock pins at the four corners of the spreader, which is hung by wire cables from the crane trolley, into inserts on upper corner fittings of the container, then twisting them 90 degrees to lock them.

The spreader is currently positioned relative to the container by remote manual operation by an operator in the crane cabin relying on visual observation. This is difficult because the visual distance from the cabin to the container is normally 20-40 m.

The container ship is moored to the quay wall, so positioning depends on such factors as tide height and

**Fig. 1.** Quayside gantry crane.

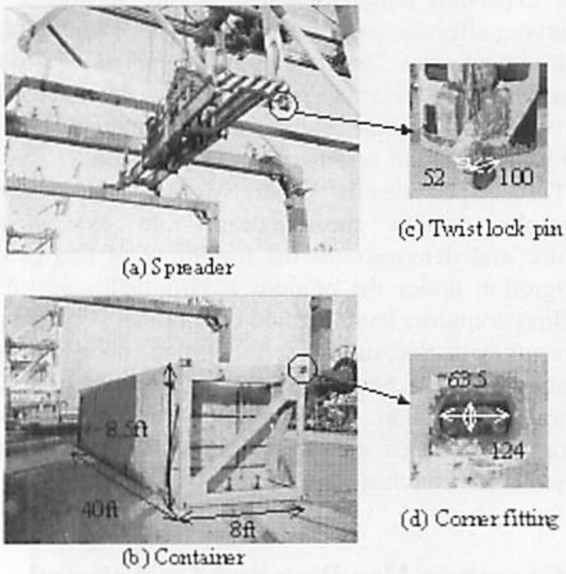



**Fig. 2.** Equipment relating to container handling.

container arrangement. Precise control of the crane spreader's position is also difficult because it is affected by the trolley position on the girder, structural deformation due to temperature changes, etc., and factors such as eccentricity in the container's center of mass and wind disturbance.

Maximum positioning precision is thus generally judged to be ±300 mm between the spreader and a container on the ship. Such precision levels make it difficult to automate container handling. And sensors suitable for directly measuring such relative positioning have yet to be developed.

### 2.2. Operational Issues in Real Environments

Container handling normally begins when a container ship docks alongside the wharf regardless of time and weather with the exception of severe storms. It would thus be desirable to be able to measure relative positioning by using pattern recognition.

Outdoor pattern recognition is generally difficult because of the brightness distribution of targets varies. This has two major causes:

(1) Changing lighting conditions, which vary with time, weather, and changing local conditions.

(2) Variations in target surface features subject to changes due to ultraviolet rays, peeling, rust, etc., that may be aggravated over time. Short-term changes also include rain drops, dirt, etc., that change a target's brightness distribution.

**Figure 3** shows the corner fitting seen from a camera on the spreader: **(a)** was taken during the daytime and **(b)** at nighttime.

Brightness distribution of the corner fitting varies widely between day and night. Technology for measuring relative positioning of the spreader and container must be able to detect this positioning under different brightness distributions.

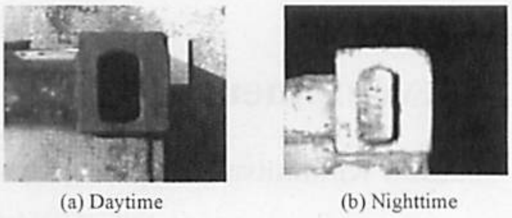



**Fig. 3.** Image of container around corner fitting.

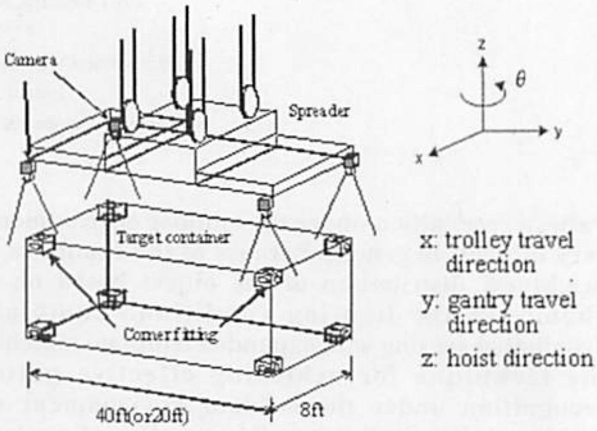



**Fig. 4.** Arrangement of cameras for distributed sensing.

## 3. Measurement Principles

To detect positioning in outdoor pattern recognition, we combined distributed sensing with pattern recognition by template matching. As detailed in the sections that follow.

### 3.1. Distributed Sensing

Since outdoor lighting conditions vary considerably, images suitable for pattern recognition cannot be necessarily guaranteed. With the camera on the spreader to handle a container, the visual field varies with the spreader's vertical movement, i.e., camera distance. It is difficult, for example, for a single camera to maintain sufficient 5mm pixel resolution and still keep the entire container in the visual field.

Since corner fittings are at each of the four upper corners of the container, a camera was positioned at each to detect the opposing corner fitting by pattern recognition of extended template matching to calculate relative positioning — trolley travel gap $\Delta x$, gantry travel gap $\Delta y$, and skew $\Delta\theta$, that is, rotation about the z-axis — of the spreader and container (**Fig.4**).

Each corner fitting is about 150 mm square and the container is a maximum of 40 ft (12 m) long. A 1-to-80 scale reduction is achieved by using corner fittings instead of the entire container for detection, making it possible to maintain both the required visual field and sufficient pixel resolution with variations of 5 m or less in camera range.

The corner fitting has interconnecting inserts on the top and both sides (**Figs.2 and 4**). Lighting condition for each corner fitting thus differs except when the sun is directly at the zenith, so the images of the four corner fittings have different brightness distributions. This can work to our advantage because the likelihood that images suitable for pattern recognition are obtained increases.

The relative position of the target container is calculated from the positions of two of the four corner fittings. The use of more than one camera increases the likelihood that the relative position is measured. If the positions of three or more corner fittings are known, any arbitrary pair of corner-fitting positions can be used to calculate the target container's relative positioning and used to evaluate the reliability of detected corner fitting positions and discarding data with low reliability, thus increasing measurement accuracy. Distributed sensing thus serves the following purposes in this study:

(1) The use of more than one camera complements image capture if one camera fails.
(2) Detection results from more than one camera are integrated to improve detection accuracy and reliability.

The likelihood of successful outdoor pattern recognition increased through the implementation of these concepts.

### 3.2. Expanded Template Matching

Template matching was used for outdoor pattern recognition for the following reasons:

(1) Based on the visual representation of the captured image, it has wide applicability.
(2) Error analysis is relatively easy compared to methods such as eigenspace in which dimensions are reduced.

Template matching detects the presence or positioning of a target normally under the same lighting conditions. An unknown input image is compared to a template, a model used as the recognition target, by evaluating their similarity using the normal correlation coefficient or some other means. The normal correlation coefficient $R(x,y)$ is given by: [4]

$$R(x,y)=\frac{\sum_{m}^{M}\sum_{n}^{N}(f(x+m,y+n)-\bar{f})(g(m,n)-\bar{g})}{\sqrt{\sum_{m}^{M}\sum_{n}^{N}(f(x+m,y+n)-\bar{f})^2}\sqrt{\sum_{m}^{M}\sum_{n}^{N}(g(m,n)-\bar{g})^2}} \quad \ldots\ldots (1)$$

where $f(x+m, y+n)$ is the unknown input image, $g(m, n)$ the target template, and $\bar{f}$ and $\bar{g}$ their mean brightness.

The presence of the recognition target is determined by evaluating normal correlation coefficient $R(x, y)$ using target judgment threshold $j^*$ as follows:

$$\left.\begin{array}{l} R(x,y)>j^* \rightarrow \text{Success detection} \\ R(x,y)\leq j^* \rightarrow \text{Impossible detection} \end{array}\right\} \quad \ldots\ldots (2)$$

Under the outdoor environment, the target's brightness distribution varies widely, so simple gray images are unsuitable for outdoor template matching. Attempts have been made to employ edge images, which are relatively robust under varying lighting condition, for template matching outdoors, but they have yet to become sufficiently practical. We improved template matching to detect the target under the outdoor environment. The binary edge image template is matched to an edge image of an unknown edge image [5]. This features the following:

(1) The primary basis of comparison is target contours, similar to conventional edge image matching, so it is relatively robust against changing lighting conditions.
(2) It more robust against image deformation (size changes or rotation) than edge image matching. Because an appropriate threshold is chosen for binarization [5].

**Figure 5** shows examples of corner fitting templates. **Fig.5(a)** is produced by normalizing and averaging four gray images captured on a cloudy day from different distances. Processing this using a Sobel operator produces the edge image in **Fig.5(b)** binarized using a threshold of 52, yielding the binary edge image in **Fig.5(c)** [5]. Images are 41×45 pixels with 1 pixel equivalent to about 4 mm.

**Figure 6** shows successful detection when the three templates in **Fig.5** were matched to 196 images of the corner fitting. Binary edge and edge image templates were matched to 196 edge images, and the gray image

(a) Gray (b) Edge (c) Binary edge

**Fig. 5.** Example of templates of corner fittings.

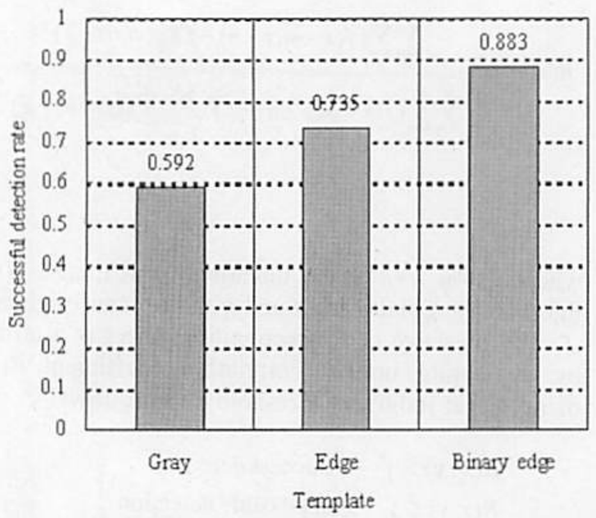



**Fig. 6.** Relation between template type and successful detection rate.

template was matched to 196 gray images. Successful detection was 0.883 for the binary edge image template, 0.735 for the edge image template, and 0.592 for the gray image template, demonstrating the feasibility of expanded template matching and indicating that its use would increase the likelihood of successful pattern recognition under the outdoor environment.

### 3.3. Detection Algorithm

**Figure 7** shows the algorithm flow for measuring the relative positioning of the spreader and container. The algorithm assumes that measurement begins when the crane's trolley reaches a position above the target container within ±500 mm of targeted trolley travel. At image input, cameras on the spreader capture images of opposing corner fittings and their location on the container, at which time crane hoist motor encoder values are recorded. Scale transformation preliminarily normalizes the size of captured images for subsequent template matching, i.e., affine transformation based on camera range calculated from encoder values of the crane hoist motor and approximate positioning data for the container. In template matching, corner fitting positions are detected as detailed in Section 3.2. In position calculation, relative positioning of the spreader and container is calculated based on position data for corner fittings obtained from template matching. This is repeated until conditions for termination are met.

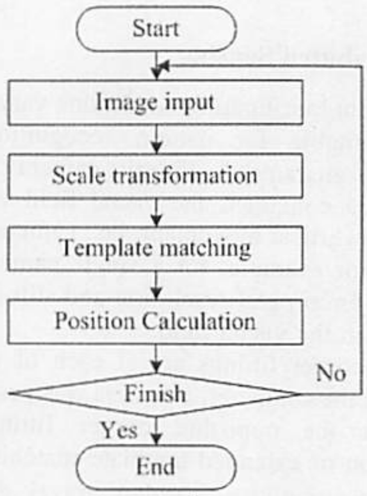



**Fig. 7.** Algorithm flow of relative position measurement.

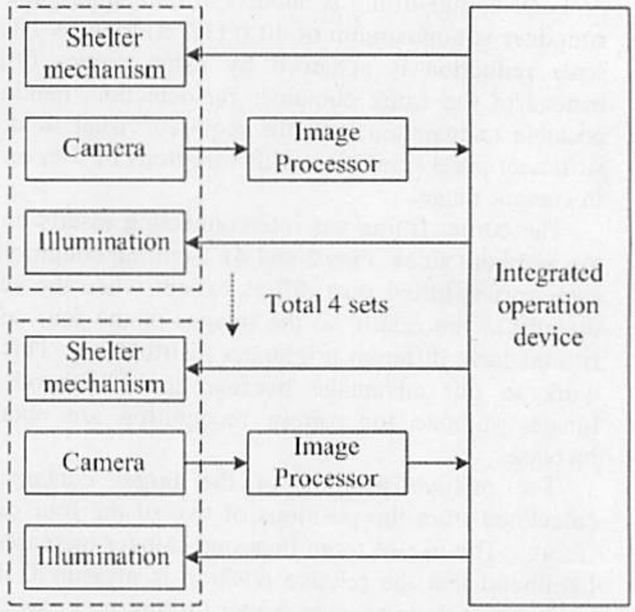


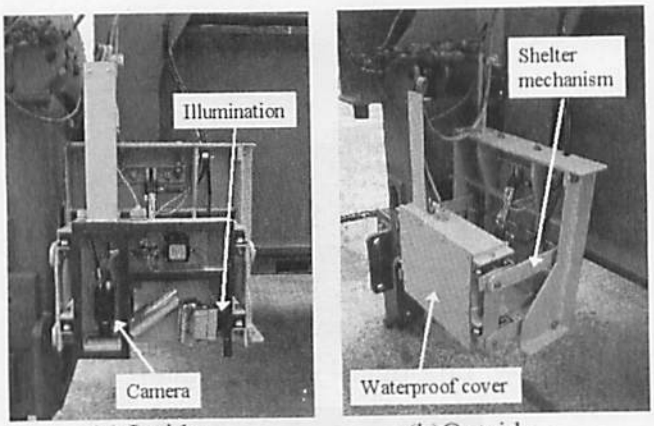

**Fig. 8.** System architecture.

## 4. System Configuration

**Figure 8** shows the system architecture of the prototype of Crane Vision incorporating the measurement principles above. The system consists of four cameras, four image processors, and an integrated operation device. The present system has two cameras, two image processors, and an integrated operation device.

**Figure 9** shows photos of the prototype camera. Inside are the illumination and camera. The camera has an electronic shutter with an automatic control to maintain mean brightness of the designated image region within a certain range.

The outside is a waterproof cover attached to a shelter




(a) Inside (b)Outside

**Fig. 9.** Camera device of Crane Vision.

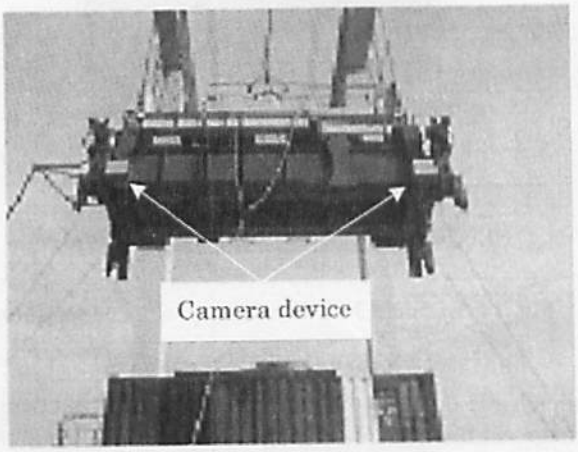


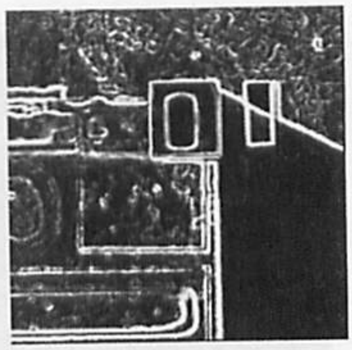

**Fig. 10.** Crane equipped with Crane Vision.

mechanism consisting of a hydraulic cylinder and parallel link to prevent collision with adjacent containers during cargo handling. The camera is normally protected by the shelter and projects from the spreader (**Fig.9(b)**) only when capturing images. The shelter is opeated by commands generated automatically based on loading information on containers on the ship and spreader positioning data.

Image signals captured by the camera are transmitted to the image processor, where scale transformation and template matching (**Fig.7**) are executed to output corner fitting positioning. Using position data for fittings, the integrated operation device then calculates relative positioning of the spreader and the target container. The result is transmitted to the crane's controller.

**Figure 10** shows a spreader equipped with crane vision. Cameras are installed on the spreader and the image processors and integrated operation device are in the crane's electrical control room.

(a) Original image 1(Clear)



(b) Detection result of original image 1

**Fig. 11.** Example 1 of detection by template matching.

## 5. Experimental Results

Crane Vision was installed on a gantry crane to test basic performance.

### 5.1. Detection of Corner Fittings

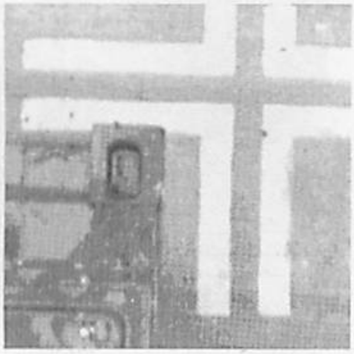
**Figures 11** and **12** show examples of detected corner fitting images, obtained by matching against the binary edge image template (**Fig.5(c)**).

**Figure 11** is a daytime image captured in clear weather, where detection was successful. The region bordered by the white frame in **Fig.11(b)** is the detected region. **Fig.12** is a daytime image captured in clear weather following rain. Corner fittings and the container are wet, and detection was judged from equation (2) to have failed.

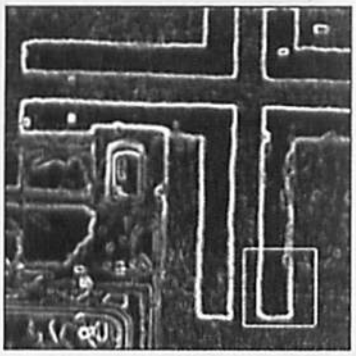
Corner fitting template matching achieved a detection precision of approximately ±2 pixels, or ±8 mm. Processing required for scale transformation and template matching was under 30 ms.

### 5.2. Effect of Weather

**Figure 13** shows the impossible detection rate for different weather conditions, where data of images captured between 09:00 and 21:00 were



(a) Original image 2(Clear)



(b) Detection result of original image 2

**Fig. 12.** Example 2 of detection by template matching.

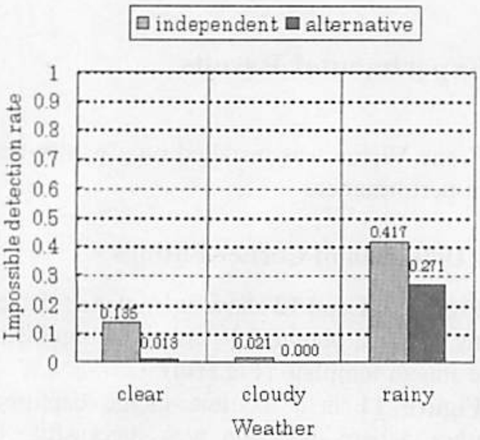
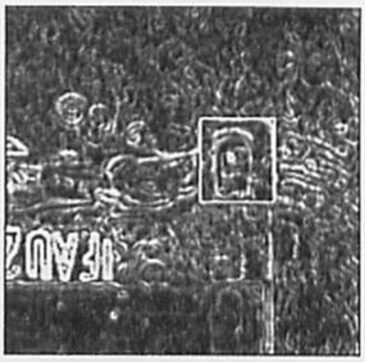



**Fig. 13.** Impossible detection rate depending on weather.

template-matched and categorized by weather. Results are given using two evaluation criteria: "independent," where images captured by the two cameras are treated as independent data, and "alternative," where successful detection with one of the two camera images captured at the same time was considered sufficient, taking advantage of the redundancy on which distributed sensing is based.

Results show that impossible detection occurs in ascending order of cloudy, clear, and rainy weather.

(a) Original image 3 (Rain)



(b) Detection result of original image 3

**Fig. 14.** Example 3 of detection by template matching.

Impossible detection is reduced when the redundancy of images in distributed sensing is taken into consideration. Relative positioning of the container is calculated successfully for about 99% in cloudy and clear weather.

In rainy weather, however, measurement fails at 27.1%. **Fig.14** shows an example of an image of the corner fitting in rain. Although the positioning of the fitting was accurately detected, it was judged a failure because the normal correlation coefficient was below the target judgment threshold of $j^*=0.414$, as is seen from the unclear contours of the container and corner fitting in the image.

**Figure 15** shows the normal correlation coefficient obtained over time under rainy conditions, where it remains below target judgment threshold $j^*$ in accord with the high impossible detection rate of the corner fitting in rainy weather observed above.

**Figure 15** also shows fluctuations in the normal correlation coefficient, which results from changes in the image pattern caused by rain. Note, however, that corner fitting edges remains still. By averaging several images, the signal-to-noise ratio (S/N) would be improved to produce a clear edge for the corner fitting. **Fig.16** shows the normal correlation coefficient plotted against the number of images used for averaging. The corner fitting is detected in rain by using an average of 35 images. This feature will be adopted in future Crane Vision systems.

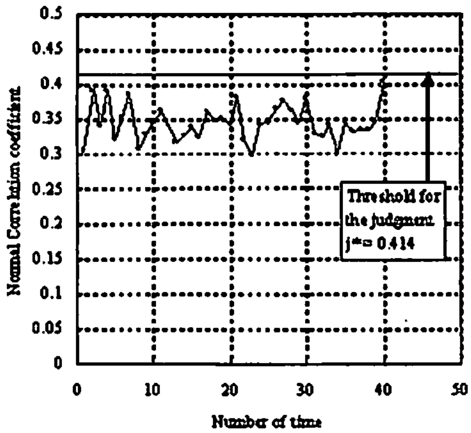



**Fig. 15.** Changes in normal correlation coefficient over time.

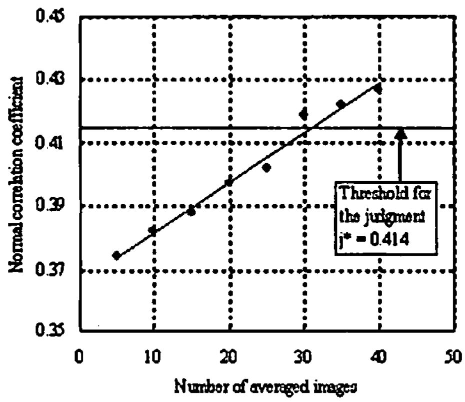
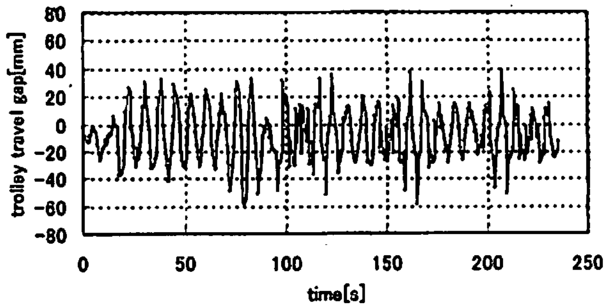
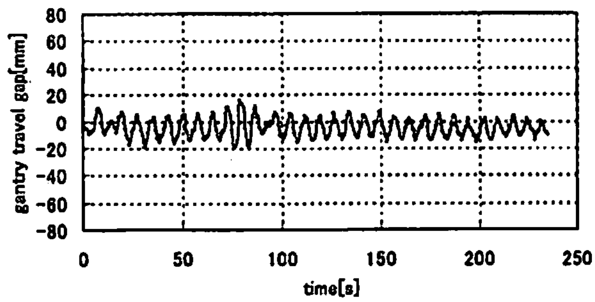


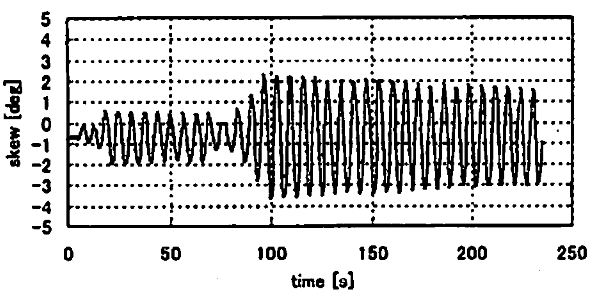

**Fig. 16.** Relationship between number of averaged images and normal correlation coefficient.




(a) Trolley travel gap




(b) Gantry travel gap




(c) Skew

**Fig. 17.** Detection example of relative position.

### 5.3. Detection of Relative Positioning

**Figure 17** shows measurements of the trolley travel gap, gantry travel gap, and skew when the spreader is rotated horizontally, i.e., skewed. Results show that Crane Vision is feasible for measuring the relative positioning of the spreader and the target container continuously.

## 6. Conclusions

To automate container handling currently done by remote manual operation by an operator relying on visual observation and thus improve container handling efficiency of quayside gantry cranes, we studied measurement of relative positioning of the crane spreader and the target container. We developed pattern recognition suited for outdoor environments by combining distributed sensing and pattern recognition by template matching. A prototype of Crane Vision was designed and fabricated, and its feasibility confirmed through experiments.

We plan to continue experimentation using Crane Vision consisting of four camera units that used improved rain-use features and to investigate ways to improve measurement reliability related to environmental factors.

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