# The 3D position recognition of multiple coils using ellipse fitting with probabilistic edge detection with stereo cameras 

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#### Abstract

The development of unmanned crane is an important issue of Factory Automation in steel industry. This paper focus on unmanned crane for picking up coils on a trailer although positions and diameters of coils is not fixed. In order to pick up those coils, unmanned crane should know exact 3D coil position. Therefore, in order to find out exact 3D coil's centers, this paper propose the system that recognize 3D position of coil center based on ellipse detection and 3D reconstruction method using stereo vision system. In details, the probabilistic ellipse oriented edge detection method and ellipse fitting method using RANSAC algorithm are proposed. Then, resolving correspondence problem using epipolar geometry and 3D reconstruction using calibrated stereo vision method are used to complete our work. Experiments show the effectiveness of the proposed method.


## 1. INTRODUCTION

In the steel works, the development unmanned crane has been important issue of Factory Automation. The crane automation have been researched for a long time and various techniques have been developed such as trajectory planning, position/velocity control, anti-swing and so forth. Among these researches, unmanned crane system which can pick up coils automatically has been needed for Factory Automation and has been researched as well.


Fig. 1. the field of coil yard
At present, an operator controls the crane 'by seeing' to pick up the coils which is located on a trailer, as shown in Fig.1. To operate the crane without any intervention of operator, the crane should recognize the 3D positions of coils to be transported. However, the positions of coils are not always same position because a trailer cannot
be parked the same place at all times. In addition, a trailer is not standardized yet with respect to height and width. Lastly, various coils with different diameters and widths are produced. In this situation, it is difficult to find 3D positions of coil centers. Given some problems of the circumstances, vision system is an effective system. Vision system can be used in many applications where the object of unknown pose and placement has to be recognized. Besides, the constraint of location to set up a vision system is lower than other systems.
This paper propose the system that recognize 3D position of coil center based on ellipse detection and 3D reconstruction method using stereo vision system. In details, the probabilistic ellipse oriented edge detection method and the ellipse fitting method using RANSAC algorithm are proposed. Then, resolving correspondence problem using epipolar geometry and 3D reconstruction using calibrated stereo vision method are used to complete our work. In experiment part, the results show accuracy, robustness and usefulness of the proposed system.
This paper is organized as follows : First, some preliminary algorithms which used in our work are described. The details about our work is represented in section 3. Finally, results of experiment are shown in section 4. Then, we conclude this paper with remarks on possible extensions for future works.

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## 2. PRELIMINARY

### 2.1 Ellipse Fitting

Given a set of points, $p_{i} \in S$, this set of points plausibly belong to a single arc of ellipse. The implicit equation of the generic ellipse can be presented as follows :
$f\left(p_{i}, A\right)=X^{T} A=a x_{i}^{2}+b x_{i} y_{i}+c y_{i}^{2}+d x_{i}+e y_{i}+f=0(1)$
where $p_{i}=\left[x_{i}, y_{i}\right]^{T}, X=\left[x_{i}^{2}, x_{i} y_{i}, y_{i}^{2}, x_{i}, y_{i}, 1\right]^{T}$, and the ellipse parameter $A=[a, b, c, d, e, f]^{T}$ which characterize the ellipse. The task is to find the parameter vector, $A^{*}$, associated to the ellipse which fits $p_{i} \in S(i=1, \cdots, N)$ best

$$
\begin{equation*}
A^{*}=\arg \min _{A} \sum_{i=1}^{N}\left[D\left(p_{i}, A\right)\right]^{2} \tag{2}
\end{equation*}
$$

where $D\left(p_{i}, A\right)$ is a suitable distance measure. This problem is called Ellipse Fitting, R. Halir et al.(1998), A. Fitzgibbon et al.(1999), T. Kawaguchi et al.(1998) and N. Bennett et al.(1999).

### 2.2 Perceptual Grouping

Human can detect many classes of patterns and statistically significant arrangements of image elements. Perceptual grouping,J. Dolan et al.(1992), R. Mohan et al.(1992), D.A. Trytten et al.(1991) and D.G. Lowe(1985), refers to the human visual ability to extract significant image relations from lower-level primitive image features (e.g. edge linked line segment) without any knowledge of the image content and group them to obtain meaningful higher-level structure (e.g. contours).
The problem is simplified by looking only at groupings of straight line segments detected in an image and by considering only those groupings that are based upon the properties of proximity, parallelism, and collinearity.

(a) proximity

(c) collinearity

Fig. 2. conditions for perceptual grouping
If two points are close together in the scene, then they will project to points that are close together in the image from all viewpoints, Fig.2(a). In the case of parallelism the line segments are presumed to overlap in the direction parallel to their orientation, whereas in collinearity the segments are expected to be separated along the direction of their orientation with an intervening gap, Fig.2(b), Fig.2(c).

```
for (i=1:max_iter)
    samples}\mp@subsup{}{i}{}=\operatorname{rand}(\mathrm{ Data, 8)
    // "8" randomly selected values from data
    Model = Model_fit(samplesi})
    err = \sum li=1 d(M Model , data j );
    // d(,): distance measure, data}j\inData,j=1,\cdots,L
    if (err < Besterr)
        M best }=\mp@subsup{M}{\mathrm{ odel }}{}
        Besterr = err;
    end
end
return M Mest
```

Fig. 3. structure of RANSAC algorithm

```
for i=1:2
(\mathcal{ROI}}\mp@subsup{}{}{i},\mp@subsup{N}{ROI}{i})=ROI_detection(I' ( )
//\mathcal{ROI}}\mp@subsup{}{}{i}\mathrm{ : A set of detected ROIs of ith image.
// N
    for j=1: N
    \mathcal{OE}}\mp@subsup{\mathcal{E}}{}{ij}=\mathrm{ EllipseOrientedEdge(I
    //ROI' }\mp@subsup{}{}{\textrm{i}}\in\mathcal{RO\mathcal{OI}}\mp@subsup{}{}{i}\quadj=1,\cdots,N\mp@code{NOI
    //\mathcal{EOE}}\mp@subsup{\mathcal{E}}{}{ij}\mathrm{ : probabilistic ellipse oriented edge image for i th
    //image, j th ROI
    (S S
    //Edge Linking & Perceptual Grouping
    // 疎ij}\mathrm{ : a set of connected edge sequences
    // Nseq}ij\mathrm{ : the numbers of sequences on j th ROI.
    (\mathcal{E}
```



```
    end //for j
end //for i
(\mathcal{Pair}},\mp@subsup{N}{\mathrm{ pair }}{})=\mp@subsup{D}{\mathrm{ correspondences }}{}(\mp@subsup{\mathcal{E}}{}{1},\mp@subsup{\mathcal{E}}{}{2}
```



```
pair}\mp@subsup{}{k}{k}={(\mp@subsup{x}{}{1},\mp@subsup{y}{}{1}),(\mp@subsup{x}{}{2},\mp@subsup{y}{}{2})\mp@subsup{}}{}{k}\in\mp@subsup{\mathcal{P}}{\mathrm{ air }}{},k=1,\cdots,N,N\mathrm{ pair
for }k=1:\mp@subsup{N}{\mathrm{ pair}}{
    P
end /// for k
return P}\mp@subsup{P}{3D}{
```

Fig. 4. Procedure of proposed system

### 2.3 RANSAC

RANSAC, M.A. Fischler et al.(1954), D.A. Forsyth et al(2003) and Hartley (2000) is an abbreviation for RANdom SAmple Consensus. It is an algorithm to estimate parameters of a mathematical model from a set of observed data which contains outliers. A basic assumption is that the data consists of inliers, data points which can be explained by some set of model parameters, and outliers which are data points that do not fit the model.
The structure of the RANSAC algorithm is as follows:

## 3. PROPOSED SYSTEM

The proposed system use stereo cameras to recognize the positions of coils. With two images obtained from each camera (left, right camera), several numbers of ellipses from each image of two cameras are detected. Then, correspondences of detected ellipses are determined with epipolar geometry. After that, the positions of coil centers with corresponding ellipses are reconstructed using triangulation of calibrated stereo cameras. Fig. 4 represents the psuedo code of our whole system.

The proposed system is composed of 2 parts broadly, as shown in Fig.5. One is ellipse detection, and Second part is 3D reconstruction of coil center obtained by ellipse detection. Ellipse detection consists of ROI detection,
probabilistic edge detection, ellipse fitting using perceptual grouping and RANSAC. The second part consists of resolving correspondence problem and 3D reconstruction of position of coil center from corresponding ellipses. Fig. 5 represents the flowchart of our whole system.


Fig. 5. Flowchart of proposed system

### 3.1 ROI detection

At first step, in order to set Region of Interest (ROI) to a given rectangle as rough center of coil we investigate distance transformation method. Coil center is dark in shadow compared to front side of coil so intensity information is useful to set ROI roughly. However, there can


Fig. 6. Selected coil's candidate
be some clusters, such as bandage, or identifier, in the center of coil. Thus, to overcome these environments we applied a distance transformation method. It is very useful to separate dark and small area connected to the center of coil. Because area of center is much wider than other clusters, we can easily cut it off in distance map. Then, we set center of rough ROI as center of gravity area. After going through these process, ROIs are obtained. For reference, a simple template matching method also can be used to detect rough ROIs. Fig. 6 shows the example of ROI detection.

### 3.2 Ellipse Fitting of coil

probabilistic edge detection In this part, at first, we perform canny edge detection within detected ROIs. As shown in Fig.7(a) and Fig.7(d), canny edge image is made up of edges due to center circle of coil (we call it ellipse oriented edge) and edges due to other parts of coils (such as bandages and wrinkles thought as noise). Our aim is to detect the ellipse from the edge image and it is important to separate the ellipse oriented edges from the noise edge, i.e. edges due to bandages and wirnkles etc., for detecting ellipse effectively and accurately. Practically, the projection of circle into 2D image form an ellipse. Besides, the direction of gradient at pixel $X_{i}$, i.e. $\theta_{X_{i}}$, with given rough center $C$ should be similar to $\angle \overline{C X_{i}}$, i.e. $\theta_{C_{i}}$, as shown at Fig.8. With this constraint, we set $P_{\text {eoe }}(X \mid C)$


Fig. 7. process of ellipse oriented gradient method


Fig. 8. Ellipse Oriented gradient
which is the probability of the pixel $X$ being the edge generated from ellipse (we call it the probability of ellipse oriented edge) with given rough center position $C$. we can derive the equation using Baye's rule as follows :

$$
\begin{equation*}
P_{\text {eoe }}(X \mid C) \propto K \cdot P(C \mid X) \cdot P(X) \tag{3}
\end{equation*}
$$

where $K$ is scale factor.
$P(X)$ means the probability of the pixel $X$ being edge

$$
\begin{equation*}
P(X)=\sqrt{\left(\frac{\partial I(x, y)}{\partial x}\right)^{2}+\left(\frac{\partial I(x, y)}{\partial y}\right)^{2}} \tag{4}
\end{equation*}
$$

which is a magnitude of gradient at pixel $X$ where $I(x, y)$ is the intensity at pixel $X=[x, y]^{T}$. In addition, the ellipse oriented probability $P(C \mid X)$ are

$$
\begin{equation*}
P(C \mid X)=\frac{1}{\sqrt{2 \pi \sigma^{2}}} e^{-\frac{\left(\theta_{C}-\theta_{X}\right)^{2}}{2 \sigma^{2}}} \tag{5}
\end{equation*}
$$

where,

$$
\begin{equation*}
\theta_{X}=\operatorname{atan}\left(\frac{\partial I(x, y)}{\partial x}, \frac{\partial I(x, y)}{\partial y}\right) \tag{6}
\end{equation*}
$$

which implies the gradient angle constraint. Fig.7(b) and Fig.7(e) show ellipse oriented probability $P(C \mid X)$, and Fig.7(c) and Fig.7(f) show $P_{\text {eoe }}(X \mid C)$ after thresholding.
ellipse fitting using Perceptual Grouping and RANSAC Although noise are reduced by applying ellipse oriented edge detection method, there still exist the noise which are not ellipse oriented and some meaningless edge segments. To remove meaningless edge segments, thus, we make the edge segments using component analysis and merge these segments using perceptual grouping with proximity and collinearity conditions. Fig.9(a) and (b) show the results of connected component analysis and perceptual grouping. In these figures, it is clear that each segments is longer than before and the noise are reduced efficiently. In Fig.9, each colored edge segment represents connected edge segments.


Fig. 9. Perceptual Grouping \& RANSAC for ellipse fitting
Given result image, Fig.9(b), we perform ellipse fitting using RANSAC algorithm and numerically stable LS ellipse fitting algorithm. At first, we sort the edge sequences in sequence length order. Then, from the longest edge sequence, ellipse fitting is done with randomly selected points (in our case, 8 points) of the sequence. If the ellipse is fitted well, some outlier (if exist) are removed and the ellipse sequence is merged to next sequence and ellipse fitting is repeated till the end of sequences. If merging of a sequence increases the error of fitting, then the merged sequence is discarded. The whole process of ellipse fitting with RANSAC is described in Fig. 10 by psuedo code.
Fig.9(c) shows the resulting edge segments which lie inside RANSAC error threshold. Then, we fit the ellipse with each resulting edge segments. Finally detected ellipse is the one which has longer segment and lower fitting error.

## 3.3 correspondence and 3D reconstruction

After detection of the ellipses in left and right image, we resolve the correspondence problem of detected ellipses,

```
function (\mathcal{E}}\mp@subsup{\mathcal{eq}}{ij}{ij})=\mathrm{ EllipseRANSAC (Seq}\mp@subsup{}{(}{ij}
// given {\mathcal{Seq}}\mp@subsup{}{ij}{{}\mp@subsup{}}{i=1}{k}\mathrm{ sorted in length order
E
Index = 
for i=1:K, i\not\inIndex
    ( }\mp@subsup{\textrm{E}}{\mathrm{ llipse }}{l},\mathcal{Seq,err ) = RANSACellipsefit (Seq}\mp@subsup{|}{i}{}
        if (err < Thresherr)
        Index = Index }\cup{i
        for j=1:K, i\not\in Index
            Seqmerge }=\mathcal{Seq}\cup\mathcal{Seq}\mp@subsup{|}{j}{
```



```
            if (err < Thresherr )
                Seq}\mp@subsup{|}{E}{}=\mp@subsup{\mathcal{Seq}}{\mathrm{ temp}}{
                Index = Index + {j}
            end
        end
        E
    end
end
return E Edetected
```

```
function (Ellipse},\mp@subsup{S}{eqtemp}{},\mathrm{ err ) = RANSACellipsefit(Seq)
```

function (Ellipse},\mp@subsup{S}{eqtemp}{},\mathrm{ err ) = RANSACellipsefit(Seq)
Nsample }=8
Nsample }=8
Itermax = 100
Itermax = 100
for i=1: Iter max
for i=1: Iter max
\mathcal{S}
\mathcal{S}
//X X}\mp@subsup{}{ij}{}=[\mp@subsup{x}{i}{},\mp@subsup{y}{i}{}\mp@subsup{]}{}{T}\in\mp@subsup{\mathcal{S}}{i}{},j=1,\cdots,N\mathrm{ sample
//X X}\mp@subsup{}{ij}{}=[\mp@subsup{x}{i}{},\mp@subsup{y}{i}{}\mp@subsup{]}{}{T}\in\mp@subsup{\mathcal{S}}{i}{},j=1,\cdots,N\mathrm{ sample
(Ellipse, Seq inlier, err)= ellipsefit( (\mathcal{S}
(Ellipse, Seq inlier, err)= ellipsefit( (\mathcal{S}
if (Ninlier < Thresherr)
if (Ninlier < Thresherr)
return {\mp@subsup{E}{llipse}{e},Se\mp@subsup{q}{inlier }{*},err}
return {\mp@subsup{E}{llipse}{e},Se\mp@subsup{q}{inlier }{*},err}
else
else
err = \infty
err = \infty
end
end
end
end
return {E [llipse},\mp@subsup{\mathcal{Seq}}{\mathrm{ inlier }}{}

```
return {E [llipse},\mp@subsup{\mathcal{Seq}}{\mathrm{ inlier }}{}
```

Fig. 10. Process of ellipse fitting using RANSAC
i.e. for a given 2-D point in the first image, it would be found the corresponding 2-D point in the second one using epipolar constraint O.D. Faugeras et al(1987)and Q. Memmon et al(2001), Fig11. To resolve the problem, we use center points of detected ellipses to determine the correspondences.


Fig. 11. Point correspondence geometry
The correspondence between two images is considered in Fig.11: for a point $X$ in image 1, we look for the point $X^{\prime}$ in image 2 it corresponds to. All possible physical points P that may have produced $X$ lie on the line between $X$ and $O$, the optical center of image 1 . As a consequence, all possible matches $X^{\prime}$ of $X$ are located on the projection of this line, i.e. epipolar line $l$ in the image 2 . In a similar way, possible match of $X^{\prime}$ should lie on epipolar line $l^{\prime}$ on image 1. That is the epipolar constraint. Epipolar constraint is represented by the equation

$$
\begin{equation*}
\mathrm{X}_{1 i}^{T} F \mathrm{X}_{2 i}=0 \tag{7}
\end{equation*}
$$

where $F$ is a fundamental matrix and $\mathrm{X}_{1 i}, \mathrm{X}_{2 i}$ is 2D image point from two cameras, respectively, and epipolar line $l$
corresponding to $\mathrm{X}_{1 i}$ is $F \mathrm{X}_{1 i}$, in similar way, epipolar line $l^{\prime}$ corresponding to $\mathrm{X}_{2 i}$ is $F^{T} \mathrm{X}_{2 i}$. Let $X$ and $X^{\prime}$ are the 2 D image points from left and right camera, respectively. If $X$ and $X^{\prime}$ are corresponding points each other (i.e. both are the projection of same point $P$ ), it should be satisfy (7). We determine the point correspondence which minimizes

$$
\begin{equation*}
\left\{\mathrm{X}_{1}, \mathrm{X}_{2}\right\}=\arg \min _{\mathrm{X}_{1}, \mathrm{X}_{2}}\left\{d\left(\mathrm{X}_{2}, F \mathrm{X}_{1}\right)+d\left(\mathrm{X}_{1}, F^{T} \mathrm{X}_{2}\right)\right\} \tag{8}
\end{equation*}
$$

where $d$ is distance measure.
After that, the 3D points $P$ of corresponding points are determined using triangulation, eqn.(9).

$$
\begin{align*}
& \left([X]_{\times} M\right) \mathcal{P}=0  \tag{9}\\
& \left(\left[X^{\prime}\right]_{\times} M^{\prime}\right) \mathcal{P}=0
\end{align*}
$$

where $M$ and $M^{\prime}$ are the projection matrix of left and right cameras respectively, and [ ] $\times$ means the cross product.

## 4. EXPERIMENT

In this section, results of experiments are shown briefly. we used 4 ccd cameras IPX2M30H(1920x1080, 33fps) for our experiments. Experiments were performed in coil yard (In POSCO) by using a working crane. As shown at Fig.12, a trailer is too long to use one set of stereo cameras. Therefore, two set of cameras are set up, and one set of stereo cameras views the front part of a trailer and other set views the rear part of a trailer.
Fig. 12 shows the configuration of our system. For our ex-


Fig. 12. configuration of our system
periments, we compare 3D position of coil center obtained by using proposed system with 3D position of gripper when the crane grips the same coil.
Fig. 13 shows results of ellipse detection. Then, using left and right images of which ellipses are detected, the correspondence problem is resolved using epipolar constraint, Fig14(a)-(d). Finally, 3D positions of coil center are reconstructed using triangulation method, Fig. 14 (e),(f). Result of our experiments is shown at Table. 1 and these show accuracy, robustness and usefulness of the proposed system.

Table 1. Accuracy of proposed system

| experiment errors (mm) |  |  |  |
| :---: | :---: | :---: | :---: |
|  | X axis | Y axis | Z axis |
| average err | 11 | 10.57 | 9.85 |
| std. dev. | 5.47 | 4.97 | 5.27 |

## 5. CONCLUSION

In this paper, the system that recognizes 3D position of coil center based on ellipse detection and 3D reconstruction method using stereo vision system is proposed. In


Fig. 13. results of ellipse detection


Fig. 14. results of experiment
particular, the probabilistic ellipse oriented edge detection method and ellipse fitting method using RANSAC algorithm are proposed. In order to end our work, then, resolving correspondence problem using epipolar geometry and 3D reconstruction using calibrated stereo vision method are used. To test our system, we compare 3D coordinate of coil center obtained by using our method with 3D coordinate of crane's gripper. We have shown the usefulness of the proposed system for the unmanned crane system or for the manned crane.
In proposed system, we just find 3D position of coil center. In future work, we would research to find 3D pose of coil with ellipse correspondence using stereo vision. Another topic for future research is to find ellipse center more accurately. In proposed system, we assume that coil center is equivalent to center of fitted ellipse. In recent researches, coil center is not equal to center of fitted ellipse. The study for solving this problem has been researched recently, JunSik Kim et al(2005), and that is another topic for future work.

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