3D Closed Loop Boundary Detection and 6 DOF Pose Estimation

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Abstract - For vision guided robotic assembly, one of the fundamental enablers is the robust estimation of 6 degree-offreedom (DOF) pose of industrial parts or subassemblies. In this paper, we present a method to estimate 6 DOF pose of automotive sheet metal panels using 3D closed loop boundary (CLB) features from a stereo vision. The 3D CLBs extracted are used to identify the corresponding CAD model and estimate its 6 DOF pose with reference to the camera frame. The novelty of the proposed method lies in the fact that 3D CLBs are extracted efficiently by matching 2D CLBs from the stereo pair with its search space confined to the region of interest (ROI) and by reconstructing only the 3D data of the matched CLBs using the epipolar constraint. Our proposed method of the 6 DOF pose estimation using 3D CLBs has been demonstrated and applied to several decklid inner panels at GM Research Lab. Experimental results indicate that the proposed method offer computation efficiency less than one second and high performance under occlusion: over success rate 90% under 15% of occlusion.

Keywords: 6DOF pose estimation, 2D/3D closed loop boundary, and stereo camera.

1 Introduction and related work

For vision-guided robotic assembly applications, a robust 6 DOF pose estimation is a critical enabler. Popular approach of object pose estimation [1] consists of 3 steps: (a) propose feature correspondences (matches) between model features and image features, (b) computing a hypothesized geometric transformation (hypothesis generation), and (c) check the agreement of image features and the transformed model features to confirm the suggested pose (hypothesis verification). This popular approach can be applied ideally to objects with rich 3D geometric features such as automotive inner panels shown in Figure 1 left.

Several methods of 6 DOF pose estimation from 3D shape features have been published recently. 3D planar surfaces and 3D cylinders [2] [3] are modelled using 3D point cloud data, and then these 3D features are used to determine the object pose by matching 3D mesh surfaces from CAD model [4]. On the other hand, several feature descriptors and matching algorithms have been extended from 2D to 3D such as Harris 3D [5] and 3D SURF [6] on 3D meshes or 3D point cloud data. Additionally, Rusu proposed the viewpoint feature histograms for fast 3D pose estimation [7]. These descriptors

are invariant to rigid body transformation, however, sensitive to noise and occlusion. Additionally they are significantly expensive in computation for 3D than 2D.



Figure 1 An example of automotive inner body panel (left) outer body panel (right)

In automotive bodyshop applications, outer body panels, as shown in Fig. 1 right, generally have non-texture or few geometric features. Thus very low number of features, key points, or descriptors such as 3D Harris and 3D SURF can be detected even with high computation time. However, inner body panels with rich 3D geometric features are ideal objects to use 3D closed loop boundaries [8] where 3D images are generated from range images by applying morphology techniques [8]. However, reflective object surfaces are not well suited for the structured light camera. For this class of objects, the stereo vision is the best choice to construct 3D features from corresponding 2D features. Several stereo camera based circular detection have been proposed to determine location of object for real-time tracking [9].

Stereo 3D reconstruction can be divided into two main approaches: dense [10] and sparse [11] stereo correspondence. The "dense" approach produces a disparity estimate at every pixel that can provide 3D information for all image region. The "sparse" is based on the corresponding 2D features. Correct correspondence between 2D features of paired images is a critical step. To reduce searching space in finding corresponding pair, an image rectification is a step where 2D projective transformations are used to form an epipolar line for depth recovery in one dimension space.

Our method is based on the "sparse" approach with 3D CLB features. Five major steps are needed to estimate 6 DOF pose of an automotive inner panel:

- Automatic 2D CLBs detection from edges extracted from two 2D images of stereo camera by Lanser's method [12] individually;
- 2) The region of interest (ROI) identification based on the epipolar constraints with working distance;
- The stereo correspondence of 2D CLBs is established in its respective ROI using the shape and size indexes, and their 3D CLBs can be reconstructed quickly;
- 6 DOF pose hypothesis generation between 3D model CLB and image CLBs;
- 5) A hypothesis and candidate transformation of 6 DOF pose for the object is generated using reconstructed 3D CLBs and 3D CLBs of CAD model. The final 6 DOF pose is selected to minimize least-square-fitting-error (LSE).

The remainder of this paper is organized as follows: we present the stereo vision setup and the algorithm overview in Section 2, followed by detailed description of 2D CLB feature extraction, ROI identification, and 3D CLB reconstruction in Section 3. Next, we outline the 6 DOF pose estimation approach in Section 4. The experimental results and algorithm performance are summarized in Section 5. We discuss our future work and conclude our paper in Section 6.

2 System and algorithm overview

Figure 2 shows the stereo camera setup with detailed parameters listed in Table 1. Each camera is a 5 megapixel digital camera, specifically Prosilica GC2450C GigE [17] from Allied Vision Technologies. The baseline distance is 140mm which was fixed for another project. This baseline distance can be increased for a better Z resolution for the decklid inner part. Similarly we can select a longer focal length than current 8.6 mm for a better X and Y resolution.



Figure 2 Camera system configuration

Table 1 Camera system configuration

Baseline Distance (B)	140 mm
Focal Length (F)	8.6 mm
Pixel Number	2448 x 2050
Pixel size (δd)	0.0034 mm
X and Y resolution	0.513 mm (at Z depth = 1.3 m)
Z resolution	4.3 mm (at Z depth = 1.3 m)
	7.5 mm (at Z depth = 1.8 m)

6DOF Pose Estimation Algorithm Overview



Figure 3 6DOF Pose Estimation Algorithm Overview

Fig. 3 above is the algorithm overview of our 6DOF pose estimation based on the stereo vision system. Halcon vision run-time environment [18] is used for 2D image acquisition from stereo cameras, 2D feature extraction, and final 3D pose display and update. We implemented an event loop with a fixed 0.5 second loop time within Halcom vision run-time environment. This means that 2D images and outputs are updated every 0.5 seconds. We developed an external library in C++ that is loaded into Halcon vision run-time event loop manager. 3D CLB construction algorithm, as described in Section 3, and 6DOF pose estimation algorithm, as described in Section 4, have been implemented in this external C++ library.

3 3D closed loop boundary extraction

To speed up the image processing time in later steps of edge detection, we used color images to segment the inner panel object (silver grey) from the background clusters. As shown in Fig. 4 below, we converted 2D images in RGB (Red-Green-Blue) color space to HSI (Hue-Saturation-Intensity) color space, and then filtered the converted images based on S value (0 to 120) and I value (120 to 255). The filtered image is then clustered to find the biggest connected cluster for the inner panel part. The smallest rectangle area that completely covers the biggest cluster is our region of interest (ROI) where all edges of the parts reside inside this rectangle.





Original Image S 0 120 I 170 255





Result

Clustering

Figure 4 Original image in RGB is filtered and segmented based on HSI values to segment and identify the smallest rectangular ROI area for the inner panel part.

Our 3D CLB extraction algorithm consists of three major steps:

- Automatic 2D CLBs detection from edges extracted from two 2D images of stereo;
- 2) the region of interest (ROI) identification based on the epipolar constraints;
- 3) 3D CLBs reconstruction based on the shape and size similarity;

We describe each of these steps in next two sections in detail.

3.1 2D closed loop boundary extraction

Closed edges usually are the openings on the inner panel whose start pixel and end pixel are the same. The definition is similar to the circle or ellipse but the shape of the closed edge are random. Edges detected by Lanser's method [12] could be closed, opened or mixed. For each edge, we perform following steps to extract closed loop:

1) Un-assign distance for all the point of a detected edge.

- Choose a point randomly, push it into a pop queue, set its distance to zero, and assign it as its parent.
- Take out a point from queue, search its neighbors and check each searched neighbor,
 - a) if it is un-assigned, set its distance to pop distance plus one, assign the taken out point as its parent, push it to pop queue.
 - b) On the other hand, if it is assigned already and assigned distance equal to distance of taken out point, then a closed loop exists. Go to Step 4.
- 4) From two points, we go back follow their parents, when their parent are same, we remove them from the edges as closed edge. Go Step 3.

Repeat (3) (4) until all points are assigned.

Fig.5 left shows the image with all edges with in ROI, the middle image is for the detected closed edges only, and

the right illustration shows the points and their assigned pop distance to detect 2D CLB. The point marked 0 is root parent, points on the edge are pushed to queue to assign distance, when the distance of taken out point and the distance its neighbor point equal(47), we start go back to find closed loop.



All edgeClosed edgeCLB searchingFig. 5. 2D Image with all edges (left) with detected CLBs only
(middle) and the pop distance assignment for CLB detection.

3.2 3D closed loop boundary reconstruction

Until now, 2D closed loop edges are obtained for both left and right images captured from the stereo camera. Some of them appear on both images, otherwise others appear on left only or on right only. To construct 3D closed loop edges, corresponding pairs of 2D CLBs should be determined first. To reduce the search area and also to increase the matching accuracy, we use epipolar rule with the minimum (Z_{min}) and maximum (Z_{max}) distance to define a region of interest (ROI) in right image for each left CLB.

Given a point, x_L , of 2D CLB in the left image, we can project this point to a 3D point at Z distance in 3D space by (1), and then project it to a 2D point (x_L) in the right image by (2) as shown in Fig.6.

$$X(\mathbf{Z}) = \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \begin{bmatrix} ZK_L^{-1}x_L \\ 1 \end{bmatrix}$$
(1)

$$x_{R} = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \cong K_{R}[R|t] \begin{bmatrix} ZK_{L}^{-1}x_{L} \\ 1 \end{bmatrix}$$
(2)

Where:

 K_L and K_R is the intrinsic matrix of left camera and right camera respectively

[R|t] is the extrinsic matrix of right camera, while the extrinsic matrix of left camera is the identity matrix.



Figure 6 Epipolar rule

For each 2D CLB on the left image, we project two CLBs onto the right image using (2) at the minimum (Z_{min}) and maximum (Z_{max}) distance. Two new projected CLBs, *CLBmin and CLBmax*, are generated as shown in Fig.7 below. The corresponding 2D CLB on the right image should be within the range between CLBmin and CLBmax. This area is our region of interest (ROI) for 2D CLB correspondence.



Figure 7 Two Projected CLBs at Z_{min} and Z_{max} distance is the Region of Interest (ROI) for the corresponding right CLB.

When several 2D CLBs exist in this ROI area, all of them should be considered as a candidate corresponding CLB. To identify precise correspondence we will search the CLBs in the bounded area using a shape similarity score $(e_{i1}^{\alpha} + e_{i2}^{\beta})$ as in (3). In other words, exactly matched CLBs satisfy two shape similarity conditions: the similarity of boundary length (N_c in pixel counts) and similarity of enclosed interior area (A_c).

$$e_{i1} = \max\left(\frac{N_{CL}}{N_{CR_i}}, \frac{N_{CR_i}}{N_{CL}}\right)$$
$$e_{i2} = \max\left(\frac{A_{CL}}{A_{CR_i}}, \frac{A_{CR_i}}{A_{CL}}\right)$$
$$\min\left(e_{i1}^{\alpha} + e_{i2}^{\beta}\right) \quad i: 0 - n$$
(3)

Where:

 N_{cL} and N_{cR} is the CLB boundary length in pixel counts for the left CLB and the right CLB respectively.

 A_{cL} and A_{cR} is the CLB enclosed interior area in pixel counts for the left CLB and the right CLB respectively.

 α , β are the control parameters (default to 2 for equal weight of both conditions).

Once the correspondence of left CLBs and right CLBs are established, we can determine point-to-point correspondence between two matched CLBs.

We first compute the central displacement d_c that is distance between the center point of right CLB and the center point of left CLB at Z_{min} . For a point (P_i^R) on the right CLB, there is a corresponding point (P_i^L) on the left CLB that is on the line defined by two points (P_i^{Lmin}, P_i^{Lmax}) as shown in Fig. 7. Corresponding pair of points on two CLBs, P_i^{Lmin} and P_j^R , satisfies two conditions in Eq.(4) below: (1) their displacement is same as the central replacement d_c and (2) P_j^R is on the line formed by two points (P_i^{Lmin}, P_i^{Lmax}) .

$$d_{i1} = \left| Dis(P_j^R - P_i^{Lmin}) - d_C \right|$$

$$d_{i2} = Dis(P_j^R, P_i^{Lmin} P_i^{Lmax}) \qquad (4)$$

$$\min(d_{i1}^{\theta} + d_{i2}^{\omega}) \quad i, j: 0 - N$$

Where:

 P_i^{Lmin} , P_i^{Lmax} are corresponding points of left CLBs at *Zmin*, *Zmax*.

 P_i^R is a point on the right CLB.

 θ , ω are the control parameters (default to 2 for equal weight of both conditions).

Once CLB to CLB correspondence and point-point correspondence on two corresponding CLBs are determined, we apply the triangulation rule to construct a 3D CLB with all boundary points. Fig. 8 below is one example result with two corresponding 2D CLBs and the resultant 3D CLB.



Figure 8 One example result of 2D CLBs and 3D CLBs

4 6 DOF pose estimation

Once we have 3D CLBs from previous steps, we can estimate 6 DOF pose of the decklid part with its CAD model.

Given the CAD model feature points M (where its ith column is a 3D point M_i , i=1,...,n) and the image feature points F (where its jth column is a 3D point F_j , j=1,...,m) from the 3D CLBs, we have a rigid body transformation relationship between these two sets of 3D points as illustrated in Eq. (5) below:

$$M = TF \tag{5}$$

Where: T is a 4 by 4 homogeneous transformation matrix that includes a 3 by 3 rotation(R) and 3 by 1 translation (t).

In order to use (5) to estimate 6DOF pose, the corespondance between the model point M_i and the image point F_j has to be given or known. Without the prior known correpondenc, an iterative closest points (ICP) [14] is a well-known method to compute the transformation matrix T[R|t]. With nosity feature data F, a least-square based fitting method [13][15] should be used. However, both methods take a long time to yield a result as they are interative methods. To speed up the 6DOF pose estimation algorithm, we can establish a good initial correspondence estimate among M and F using their shape similarity as shown in our algorithm flow chart in Figure 9 below.



Figure 9 6DOF pose estimation algorithm

For each CLB, we compute its centeral 3D position \overline{F} and \overline{M} as the average position of all CLB boundary points in the feature set and in the model set respectively.

$$Mi' = [M_i - \overline{M}] \quad (6a)$$

$$Fi' = [F_i - \overline{F}] \quad (6b)$$

We use similar shape to check all possible cases. This will significantly reduce the number of candidate pairs. For each similar shaped CLBs, the least square error between model and object is computed. Assume that, M' is a matrix form of points M'_i of n points of model with each column for one point on model CLB, and F' is matrix form of points F'_j of m

points of image features with each column for one point on feature CLB, Eq. (5) becomes Eq. (7) below:

$$M' = TF' \tag{7}$$

When the correspondence of n points are known by the shape similarity test, we can compute the singular value of decomposition [16] of the least square error fitting as in (8) below:

$$M' * (F')^t = VSU^t \tag{8}$$

Where: V and U^t are orthonormlaized engine vectors associated with n largest eigenvalue in S.

Then the rotation matrix and the translation vector can be estimated by

$$R = VU^{t}$$
(9)
$$t = \overline{M'} - R\overline{F'}$$
(10)

The least square fitting error is computed for all candidate transformation T[R,t] and the one with the minimum least square error is chosen as final estimated 6DOF pose.



(c) Estimated 6DOF pose with the minimum least square error *Fig. 10. One Example of 6DOF Pose estimation.*

5 Experimental results and performance

In this section, we evaluate the performance of our algorithm for both computation and accuracy. The first major part in our algorithm is the 3D CLB reconstruction from two stereo images as detailed in Section II. Our 2D CLB matching and 3D CLB reconstruction has a better performance than two well-known methods, sum of absolute differences (SAD) and sum of squared differences (SSD), for stereo matching in term of measuring mean distance error (MDE). We use the window size 9x9 and find the minimum cost along the epipolar line from *Zmin* to *Zmax* with the 2 pixel gap. We set parameters α , β , θ , ω to 2 for equal weights for all four factors. Both 3D methods search the corresponding points in limited area defined by epipolar constraint and the known range of CLB

depth. We vary the object's position in two directions: linearly along camera Z axis up and down by 10 cm and rotationally about the Y axis by 3 degree. Figure 11 below shows the mean distance error (MDE) of our method in comparison with SAD and SSD methods for the translational position change (upper graph) and rotational position change (lower graph)



Fig. 11. Mean distance error (MDE) of our method in comparison with SAD and SSD

The second major part in our algorithm is the 6DOF pose estimation from the image 3D CLBs and the model 3D CLBs. To evaluate accuracy of 6DOF pose estimation, we rotate the object's position about the camera Z axis by 6 degree for 60 increments to complete the whole 360 degree rotation at the fixed Z distance (1.5m). Our model is consisted of 50 CLBs with 15 of them that are bigger than 2.5cmx2.5cm. These big CLBs play a bigger role to the 6DOF pose estimation than other remaining CLBs since they have significant shape information while smaller shapes are not distinguish enough and mainly used for calculate least square fitting error.

Table 2 Error in Estimated 6DOF P	Pose
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	Euclidean						
	Distance						
	Error	Х	Y	Ζ	α	β	(dag)
	ratio	(mm)	(mm)	(mm)	(deg)	(deg)	(deg)
Our	7.52 mm /						2.56
	5 mm	3.21	3.12	6.14	1.67	1.74	2.30
Y.Lee[8]	1.8 mm/						
	0.4 mm	1.4	0.8	0.5	-	-	-

Table 2 above lists the comparison of our estimated 6DOF pose with Lee's method [8]. Our method use stereo camera to test the decklid object shown in Fig 1.a at 1.5 m,

Lee's method use high quality camera to test object in working distance from 1m to 1.5m.

The large positional error along X, Y, and Z in our method is most due to the resolution in our stereo camera setups. A high quality camera is used in Lee's case [8]. Therefore it is not a equivalent comparison. However, if we use a ratio to normalize the depth resolution in each camera system, the ratio of Euclidean distance error and the depth resolution, our method yields the ratio of 1.5 (7.52mm/5mm) which is better than the ratio of 4.5 (1.8/0.4) in Lee's method.

In addition, we also verified the performance of our 6DOF pose estimation with occlusion. As the number of CBLs are occluded, the estimated pose success rate will decrease as expected. At fixed Z distance of 1.5 m, we vary the object's position in X direction as a portion of the object is out of the view gradually. Fig.12 is the graph which shows the decreased number of valid CLBs (upper) where Num of REC indicate big CLBs and the reduced success rate (below) for the estimated 6 DOF pose. The success rate from 0 to 30% of occlusion obtained from experiments, and this value from 30% to 50% of occlusion is estimated.



Figure 12 Estimated 6DOF Pose Performance with occlusion

Our method can be used in real-time application with the total computation time at 1.0 second. Roughly 0.85 second is for two 2D CLB extraction (0.5 seconds) and CLB correspondence (0.35 seconds) in Halcon run-time environment. 6DOF pose estimation using 3D CLBs takes 0.15 seconds with a DLL library written in C++.

6 Conclusion

In this paper, we present a fast and robust method to estimate 6 DOF pose of automotive inner panels using 3D CLBs from a stereo vision. First, 2D closed loop boundaries are extracted from two RGB images of the stereo pair. Next, the region of interest (ROI) in the paired image is determined based on the epipolar constraints within the known working distances. Then, the stereo correspondence of 2D CLBs is established in its respective ROI using the shape and size indexes, and their 3D CLBs can be reconstructed quickly. Finally, a hypothesis and candidate transformation of 6 DOF pose for the object is generated using reconstructed 3D CLBs and 3D CLBs of CAD model. The final 6 DOF pose is selected to minimize least-square-fitting-error (LSE).

We evaluate the performance of our 6 DOF pose estimation algorithm and demonstrate that the mean distance error (MDE) of our method is better than two well-known methods, SAD and SSD. However, the absolute error in our results is worse than Lee's method due to the poor depth resolution (the z resolution is 5mm at z = 1.5 meters). When measured by normalized error, i.e. with mean distance error to depth resolution ratio, our method performs better. We also evaluate the occlusion effect on the appearance of 3D CLB features and pose correct rate. As expected, these performance deteriorates as the number of distinguish 3D CLBs decreases from 12 to 4.

Our 6DOF pose estimation algorithm is fast, within 1 second, to be used for real-time applications. We have applied this method to several decklid inner panels at the manufacturing research lab, GM Global R&D Center, Warren, MI, US.

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8 References

- Haralick, R. M., Joo, H., Lee, D., Zhuang, S., Vaidya, V. G., & Kim, M. B. "Pose estimation from corresponding point data". Systems, Man and Cybernetics, IEEE Transactions on, 19(6), 1426-1446, 1989.
- [2] Nguyen, H. H., Kim, J., Lee, Y., Ahmed, N., & Lee, S. "Accurate and fast extraction of planar surface patches from 3D point cloud". In Proceedings of the 7th International Conference on Ubiquitous Information Management and Communication (p. 84). ACM, Jan ,2013.
- [3] Schnabel, R., Wahl, R., & Klein, R. "Efficient RANSAC for Point-Cloud Shape Detection". In Computer graphics forum (Vol. 26, No. 2, pp. 214-226). Blackwell Publishing Ltd, June, 2007.
- [4] Kim, J., Nguyen, H. H., Lee, Y., & Lee, S. "Structured light camera base 3D visual perception and tracking application system with robot grasping task". In Assembly and Manufacturing (ISAM), 2013 IEEE

International Symposium on (pp. 187-192). IEEE, Jul 2013.

- [5] Sipiran, I., & Bustos, B. "Harris 3D: a robust extension of the Harris operator for interest point detection on 3D meshes". The Visual Computer, 27(11), 963-976, 2011.
- [6] Knopp, J., Prasad, M., Willems, G., Timofte, R., & Van Gool, L. "Hough transform and 3D SURF for robust three dimensional classification". In Computer Vision–ECCV 2010 (pp. 589-602). Springer Berlin Heidelberg, 2010.
- [7] Rusu, R. B., Bradski, G., Thibaux, R., & Hsu, J. "Fast 3d recognition and pose using the viewpoint feature histogram". In Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on (pp. 2155-2162). IEEE, October, 2010.
- [8] Lee, Y., Lee, S., Kim, D., & Oh, J. K. "Improved industrial part pose determination based on 3D closedloop boundaries". In Robotics (ISR), 2013 44th International Symposium on (pp. 1-3). IEEE, Oct 2013.
- [9] Yoon, Y., DeSouza, G. N., & Kak, A. C. "Real-time tracking and pose estimation for industrial objects using geometric features". In Robotics and Automation, 2003. Proceedings. ICRA'03. IEEE International Conference on (Vol. 3, pp. 3473-3478). IEEE. Sep, 2003.
- [10] Scharstein, D., & Szeliski, R."A taxonomy and evaluation of dense two-frame stereo correspondence algorithms". International journal of computer vision, 47(1-3), 7-42, 2002.
- [11] Loop, C., & Zhang, Z."Computing rectifying homographies for stereo vision". In Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on. (Vol. 1). IEEE, 1999
- [12] Lanser, S., & Eckstein, W. (1992). "A modification of Deriche's approach to edge detection". In Pattern Recognition. Vol. III. Conference C: Image, Speech and Signal Analysis, Proceedings., 11th IAPR International Conference on (pp. 633-637). IEEE. 1992.
- [13] Arun, K. S., Huang, T. S., & Blostein, S. D. "Leastsquares fitting of two 3-D point sets". Pattern Analysis and Machine Intelligence, IEEE Transactions on, (5), 698-700, 1987.
- [14] Paul J. Besl and Neil D. McKay. "A method for registration of 3-D shapes". IEEE Transaction on Pattern Analysis and Machine Intelligence, 14(2):239–256, 1992.
- [15] Estépar, R. S. J., Brun, A., & Westin, C. F. "Robust generalized total least squares iterative closest point registration". In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2004 (pp. 234-241). Springer Berlin Heidelberg, 2004.
- [16] Golub, G. H., & Reinsch, C. Singular value decomposition and least squares solutions. Numerische Mathematik, 14(5), 403-420, 1970.
- [17] Prosilica GC2450 Camera from AVT GugE http://www.alliedvision.com/en/products/cameras/detail/2 450.html
- [18] Halcom Vision Run-time Engine http://www.halcon.com/halcon/hdevelop/hdevengine.htm 1