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Vision Based Component Identification with Template Matching and Vector Classification

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Abstract: The paradigm of fully automated product assembly and manufacturing is yet far away from the practice and one of the essential infrastructures for this idea is the component identification and recognition system which is best to be done visually. At this study, we present a template matching system which is able to discover the presence and confirm the existence of certain components on the line.

Key words: Component recognition, computer vision, template matching, infrastructures, identification

INTRODUCTION

The idea of robotic manufacturing line requires many sub systems. One of the most fundamental subsystems could be a computer vision algorithm which can identify the component presence at the scene and estimate its position-orientation. While the current researcher has extensively discussed the methods of position and orientation estimation at a previous research but that discussion exposed the implicit fact that the first stage of component identification may need further details and discussion, hence at the current work we are prepared to explain more about the applicable component recognition method.

As is explained by Anil Jain and Lihong Zheng and Xiangjian He after preprocessing there are many extractable features for each region and we will need a strategic view to determine which features to be considered as most ascertaining ones like what is argued by Gadat and Younes (2007). There are even feedback architectures designed for the matter of feature weighting like by Jeong *et al.* (2010). Eventually pattern recognition methods can be designed and classified based on many aspects of those which are even more deeply debated by Rao and Reddy (2011). At the presented work after skimming the various references and exhibited strategies we have decided to utilize template matching path to determine the similarity of the patterns and supervised feature feedback strategy to identify the most deterministic features of both templates and observed patterns to be compared.

PRESENTED APPROACH

In order to obtain a better comprehension of this section first we need to bid a more accurate survey over the pattern recognition fundamentals and also to more explicitly realize our goal at this project.

As mentioned above we need to discover and confirm the existence of the components at the work environment and it appears that the task can be best handled through intelligent vision systems. Like the living organic systems which are always looking after previously known patterns or try to conform innovative ones a computer vision system has to imitate this. From mathematical and hierarchical point of view there can be many modelings, analysis and approaches presented for these procedures and we are going to establish a supervised trained template matching pattern recognition here.

Over all pattern recognition systems can be categorized based upon the theories utilized at their three prominent stages of preprocessing, training and classification. At the preprocessing level the developer person faces a wide inventory comprised of many extensively developed and conventional image processing and segmentation-labeling algorithms. While this part is not the topic of study here the next level catches more notion; a trained and prepared pattern identifier and classifier can has been designed with various categorized strategies like template matching, statistical arbitration, fuzzy criterions or even syntactic pattern recognition. However, all of these perform by

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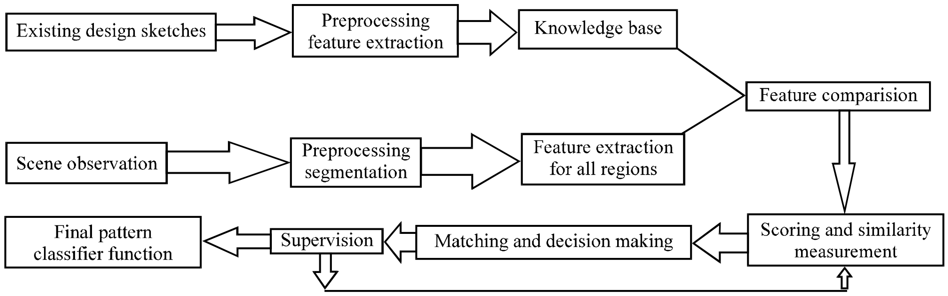

Fig. 1: The training flowchart

assigning certain weights to some of the extractable features of each labeled segment at the image. The role of the training phase is only restricted to regulate the amount of weighting factor dedicated for each observed feature in order to best classify and identify the pattern and this is often achieved through supervised adaptation of voting matrixes which can omit or amplify the credibility of each feature's role at the final decision making step. At this work while our templates which are indeed the sketches of previously designed industrial component are to be matched with the segments of observed scene; now these already drawn sketches bear only a few extractable and reliable features which makes the task much less complicated. We actually only have to regulate the amount of importance score allocated for each feature in order to obtain a confident matching result; this will eventually lead to the establishment of a similarity measurement function. The job implies to be more complex than what was deemed when we remind that at the practice the components might have been thrown at random location and orientation and the perspective effect could cause a simple matching system to quickly fail because the patterns belonging to each face of the components are now deformed. One immediate solution come across the mind is to rotate each region utilizing the Euler rotation matrix but this will be a time consuming challenge especially where we have to compare all discoverable segments to each sketch design of each subjected component. A far more rapid and trustable solution is required here. However, at Mahdi Vaezi we illustrated that after the task of pattern identifier algorithm is executed and the matching results are in hand we can rotate the regions of observed scene and compare them to the coupled segments of original designs in order to pin point the actual orientation of the component at the work table. With respect to what is yet explained a flowchart of designated strategy can be presented as in Fig. 1.

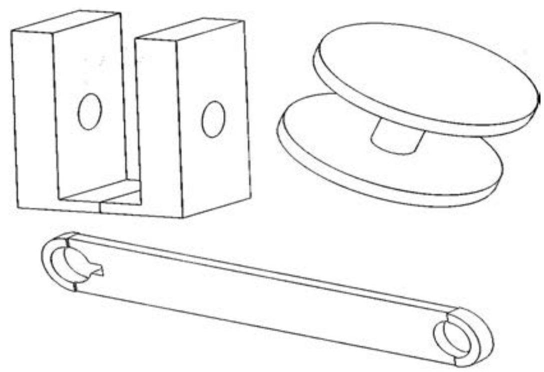

Fig. 2: Our components utilized for the current job

CURRENT EXPERIMENT

Data extraction and special arrangements: Based on the interpretation strategy explained above now we try to put the notion in practice. For this first we have drawn three components shaped at the most commonly observable scheme around the manufacturing lines, those are a rode shaped, a circle shape and a cubic square shaped component with some extra details to make a challenge, the parts are depicted in Fig. 2 with a random position-orientation allocation as it would be at an assemble work table.

Now we need another set of the images and those are the design sketches. We acquire standard sketch views from top, right and front for each component while the scales are also known. Not an extra ordinary requirement when the industrial components certainly have blueprints (Fig. 3).

The next step is to separate the sketches and current views to segments, the regions extracted from the sketches are the reference ones and those which conceived from the current view are the objective ones which should be compared with the sketch segments and recognized. The results are exhibited in (Fig. 4-6).

First and before we attend to extract the regions of current view image we need to categorize different areas belonging to different objects on the table into their belonging and yet unidentified object. In order to do so we can simply breakdown the current view image to several pictures which each one contains only one assigned object's fit and align the obtained regions with those locations. This will reduce the complexity of the upcoming steps. The results of detent region extractions are shown in Fig. 7 and 8.

It should be also noticed that some of the extracted regions may not even belong to the object and are created due to the imaging circumstances like some of the segments seen on Fig. 9. We did not remove those in order to maintain more creditability and robustness for our work.

According to scheme plan flowchart illustrated as Fig. 1 we now need to extract all existing region properties of sketch segmentation as a reference knowledge base and then do the same for each observed object segmental portions. After that we shall compare data base of all current view objects with each sketch group and inspect for similarities. A voting system will be employed and supervised to be modified for better results. The measurable features like any template matching technique for each region which can be relied on and don't vary with respect to the perspective are the quantity of the corners (or flanks), the ration between longest and shortest diameters, the ratio of pixels in the region to pixels in the

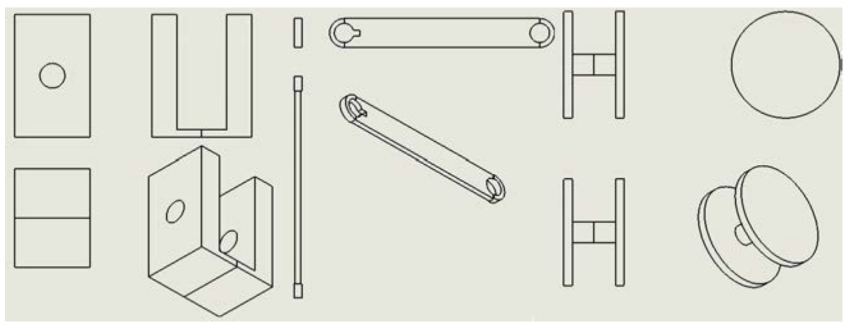

Fig. 3: Design sketches of each component

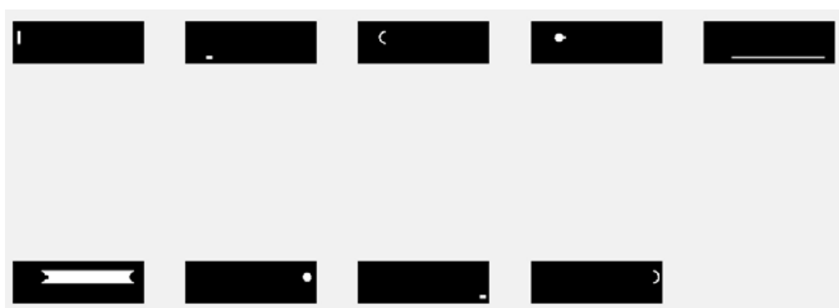

Fig. 4: Sketch regions of rode component

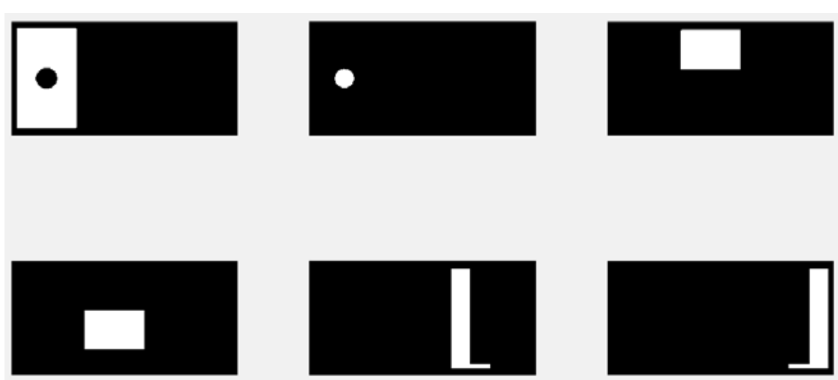

Fig. 5: Sketch segmentation of base component

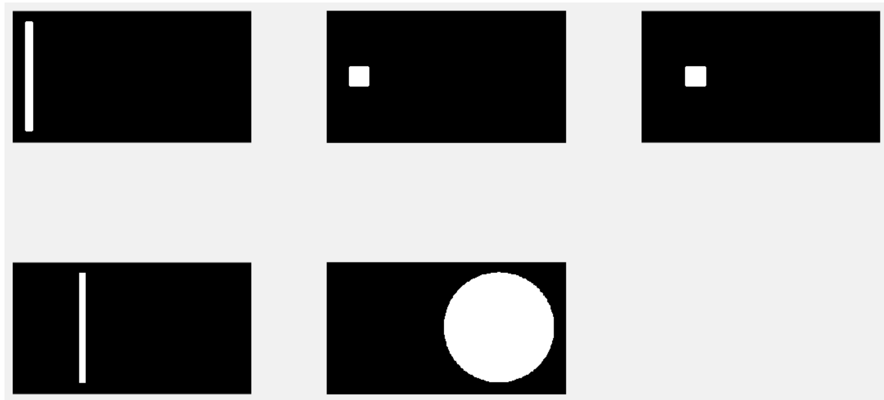

Fig. 6: Sketch segmentation of slider component

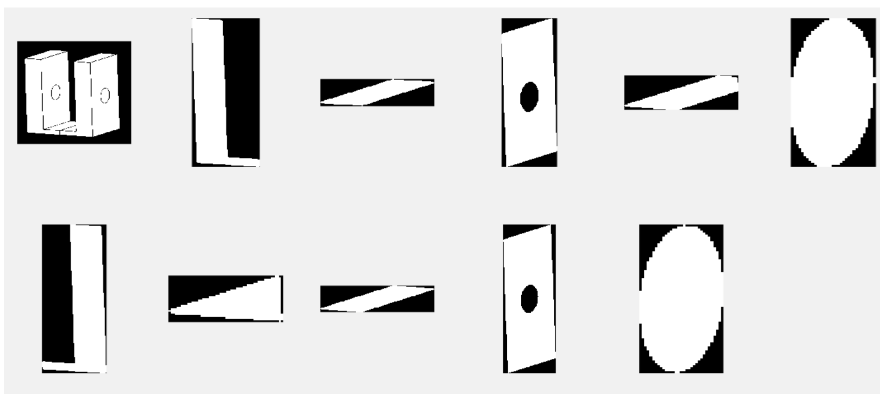

Fig. 7: Segmentation of object 1 at the current view scene, assuming that we don't yet know which component sketch design could this object match with

Fig. 8: Segmentation of object 2 at the current view scene

Fig. 9: Segmentation of object 3 at the current view scene

Table 1: Pattern features of Rode component sketches

Object rode	Seg. 1	Seg. 2	Seg. 3	Seg. 4	Seg. 5	Seg. 6	Seg. 7	Seg. 8	Seg. 9
F1	4.000	4.000	4.000	4.000	4.000	12.000	0.000	4.000	4.000
F2	4.391	1.994	2.377	1.282	43.110	6.304	1.001	2.094	2.374
F3	0.991	0.980	0.358	0.663	0.998	0.937	0.811	0.981	0.373
F4	2.000	2.000	2.000	1.000	2.000	3.000	0.000	2.000	2.000

total bounding box and some other and more difficult to probe features like the number of parallel flank pairs. As for the current preliminary work we content on these four renamed as F1-F4. Table 1-6 contain the data about these four features extracted from each object's segments.

Corners could be extracted base on corner detection algorithm described by Willis and Sui (2009) but this and similar methods usually point at many pixels which only have one black neighbor as corners while it's not beneficial for this pattern recognition task there for we considered abolishing the unnecessary corners. To do so we associated the straight lines detection method (Duda and Hart, 1972) to extract the flanks. The flanks which would not possibly cut each other even if extended were assumed as parallel pairs and the cross points were considered as corners. For each L_1 (x_1, y_1) and L_2 (x_2, y_2) pixels at the same line we could write the straight line equation:

$$y-y_1 = \frac{y_2-y_1}{(x_2-x_1)}(x-x_1) \qquad (1)$$

By extending this equation we could discover possible cross points, the existence of cross points would reject the comprised flank pair to be a parallel one and if the coordinate of the cross points were aligned with a white pixel at the subjected segment this was a corner. No need to remind that the curves are excluded from this because even parallel curves may look like crossing at certain view angles. While the curves can also be spotted (Olson, 1999) at the image we neglect curvy flanks and their cross points to avoid mistakes. In cases of circle shapes we can rely on other two measures.

Table 1-3 are used as knowledge base and Table 4-6 as current extracted features. The next step would be to compare the features of each current view's segment with the knowledge bank and to design a suitable voting formula to recognize each region and component.

There is also another useful important parameter to recognize the components and that's the neighboring regions. This means that if one region is matched with a sketch then the adjacent region must also match with one of the adjacent sketches despite of the direction. Utilizing this feature will prevent mistaking different components

Table 2: Pattern features of base component sketches

Object base	Seg. 10	Seg. 11	Seg. 12	Seg. 13	Seg. 14	Seg. 15
F1	4.000	0.000	4.000	4.000	6.000	6.000
F2	1.672	1.004	1.513	1.513	4.383	4.348
F3	0.941	0.784	0.999	0.999	0.519	0.513
F4	2.000	0.000	2.000	2.000	4.000	4.000

Table 3: Pattern features of slider component sketches

Object slider	Seg. 16	Seg. 17	Seg. 18	Seg. 19	Seg. 20
F1	4.000	4.000	4.000	4.000	0.000
F2	13.910	1.000	1.032	15.170	1.000
F3	0.998	0.996	0.996	0.998	0.786
F4	2.000	2.000	2.000	2.000	0.000

with similar sketches. However, at this work we focus on recognizing the shape of segments and this part will be kept for further developments.

Also, one of the most troublesome situations is when a region is hindered by other objects or regions. At such cases the area is most likely unrecognizable not only for this method but also for accustomed human mind. To resolve such a situation unrecognizable segments will be put aside and attention will be concentrated at the surrounding ones. It means that if one region and at least one of its neighboring regions are matched with the corresponding sketches then the object is most likely the same component but to be assured the manipulator may be tasked to relocate the object for further inspection.

Similarity measurement and pattern matching: As illustrated at Fig. 1 after gathering the required data it's now turn to establish a standard similarity measurement approach. Even though template matching methods have been widely discussed before but most of the formulations belong to measure the pixel properties of image in order to find most similar photos while we require a pattern feature based comparison to assess the observed objects. For this purpose little investigations are yet made. A conventional and very similar work is presented at (Aljarrah *et al.*, 2012) where the authors have tried to discover the identity of chessmen on the board but instead of attending the geometric features like corners and axis it only performs on the relation between the black and white pixels at each square of the board.

At this work, we can consider a 4D space to put each region at. While it is not possible to depict a 4D coordinate system yet we assign each sketch segment of original designs an identity vector called as SV_i which is

Table 4: Pattern features of observed object 1 segments

Object 1	Seg. 1	Seg. 2	Seg. 3	Seg. 4	Seg. 5	Seg. 6	Seg. 7	Seg. 8	Seg. 9	Seg. 10
F1	6.000	4.000	4.000	5.000	0.000	6.000	3.000	4.000	4.000	0.000
F2	4.894	5.211	3.254	4.270	2.208	4.784	2.446	5.219	3.460	2.180
F3	0.468	0.413	0.780	0.477	0.778	0.510	0.538	0.412	0.778	0.770
F4	4.000	2.000	2.000	2.000	0.000	4.000	0.000	2.000	2.000	0.000

Table 5: Pattern features of observed object 2 segments

Object 2	Seg. 11	Seg. 12	Seg. 13	Seg. 14	Seg. 15	Seg. 16	Seg. 17	Seg.18	Seg.19	Seg. 20	Seg. 21
F1	4.000	0.000	3.000	5.000	12.000	4.000	3.000	0.000	0.000	4.000	4.000
F2	2.994	2.790	3.272	2.098	5.780	57.560	1.221	3.335	2.314	3.003	3.444
F3	0.324	0.401	0.510	0.475	0.367	0.068	0.560	0.319	0.588	0.326	0.312
F4	0.000	0.000	0.000	0.000	3.000	2.000	0.000	0.000	0.000	0.000	1.000

Table 6: Pattern features of observed object 3 segments

Object 3	Seg. 22	Seg. 23	Seg. 24	Seg. 25	Seg. 26
F1	2.000	6.000	2.000	0.000	4.000
F2	5.411	2.776	5.428	2.128	1.273
F3	0.145	0.522	0.145	0.685	0.678
F4	0.000	1.000	0.000	0.000	1.000

invariable and constant on the dimensions. On the other hand, each region of current view objects is assigned a vector CV_j which is indeed a vector of variables depending on the angle of view which is unknown yet. But there is still more to be considered. Although, many facial features of these pattern may change due to the direction of view yet the quantity of corners never alter unless if the object is hindered by another which totally makes the region undeterminable (Bober, 2001). Hence before inspecting further we make an initial categorization based on the amount of corners. SVs and CVs with same number of corners are put at same 3D spaces. While we have 46 total number of regions those can be subcategorized to sets of 0, 3, 4, 5, 6, 12 cornered regions. At each space the SVs are presumed reference and CVs as measures. Then we will count the direct distances of each measure with each references and choose the most probable matching pairs. But how to evaluate remaining three features to assess the distance and similarity? The three features are the ration between longest and shortest diameters which is the least reliable and most likely to vary, the ratio of pixels in the region to pixels in the total bounding box and the number of parallel flank pairs. Since, the nature of these features is different we assume granting different weights for each. It means that when putting on the scale the sample $Sv_i = (af_{2i}, bf_{3i}, cf_{4i})$ may change in distance according to our supervising perception of similarity. The distance between these is counted according to the Weighted Euclidean Distance (WED):

$$SV_i \rightarrow CV_j = \sqrt{\left(a\left|f_{2i}-f_{2j}\right|\right)^2+\left(b\left|f_{3i}-f_{3j}\right|\right)^2+\left(c\left|f_{4i}-f_{4j}\right|\right)^2}$$

Pre-categorization based on the number of corners eventually causes much reduction at the bulk of efforts. Now instead of 20×26 possible combinations of SVs and CVs we have to deal with only a few of all possible pairs. The zero cornered shapes (Ellipsoids) are restricted to SV_7, SV_{11}, SV_{20}, CV_5, CV_{10}, CV_{12}, CV_{18}, CV_{19}, CV_{25} which bears only 18 possible pairs. Furthermore there are no 2, 3 or 5 cornered shapes at the sketches there for all these regions at current view images are discarded. However, we still have many 4 cornered shapes. Those are $SV_{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 13, 16, 17, 18, 19}$ and $CV_{2, 3, 8, 9, 11, 16, 20, 26}$ which can comprise 126 possible cases. 6 cornered regions are $SV_{14, 15}$, $CV_{1, 6, 23}$ (6 pairs) and finally we have only one pair of 12 cornered regions (SV_6, CV_{15}). Thus, instead of 520 pairs we only have to probe among 150 candidates. Now our classification stage faces 150 input pairs, 3 weight variables and 17 output (correct) pairs. Each one of input pairs have a dedicated score (distance) which depends of the weights and the weight must be regulated in a mode that which can bring the top 17 choices.

Classifier training: While we have yet reduced the dimensions of features space into subcategories but we are not going to get the training set further reduced because it would not be a best idea to train separate classifiers for each class of corners. We need a classifier which can separate the input shapes into individual pairs even if we don't decline some of the possible cases. So, we are going to put all the training data together at the task. The 150 candidate pairs distances are going to be scoped for each possible set of "a, b, c" factors and a set which leads to a minimum distance only among 17 target pairs must be found. This method is practically a modification of k-nearest-neighbor classification method (Buttrey and Karo, 2002). The presented classifier training algorithm works upon these principles:

- 'a' is always smaller than 'b' and 'c'
- Assume a range of positive variation for the elements
- Calculate the WED amount for each 150 pairs

- If the WED of the 17 goal associates are smaller than all the other 133 candidates then the current set of "a, b, c" is a practicable classifier set. Should the answer can't be found at the current range but there had been cases where over half of the pairs passed the condition we should reduce the step of changes around the point. Furthermore we must widen the range at the positive direction to find an answer. For the current experiment a possible answer could be spotted at (0.43, 0.71, 0.64)

CONCLUSION

After a successful classifier development now we can obtain a matched sketch among the observed scene's extractable regions. According to our previous work at atleast 3 matches at the unknown object should be enough to select the object as most likely a match for a known component. Once the match is found it is possible to inspect more for the precise amount of imposed rigid three dimensional rotations so the direction of the component on the table can be fully determined. The direct distance can also be discovered by comparing the current view's lengths with the original sketches.

There are virtually no restrictions for the further improvements here. There had been several stages at the duty like the preprocessing and edge detection-region extraction, features selection and evaluation, classification strategy and training phase and the approach of dealing with the unidentifiable areas.

REFERENCES

Aljarrah, I.A., A.S. Ghorab and I.M. Khater, 2012. Object recognition system using template matching based on signature and principal component analysis. Intern. J. Digital Inform. Wireless Commun., 2: 156-163.

Bober, M., 2001. MPEG-7 visual shape descriptors. IEEE Trans. Circuits Syst. Video Technol., 11: 716-719.

Buttrey, S.E. and C. Karo, 2002. Using k-nearest-neighbor classification in the leaves of a tree. Comput. Stat. Data Anal., 40: 27-37.

Duda, R.O. and P.E. Hart, 1972. Use of the Hough transformation to detect lines and curves in pictures. Commun. ACM, 15: 11-15.

Gadat, S. and L. Younes, 2007. A stochastic algorithm for feature selection in pattern recognition. J. Mach. Learn. Res., 8: 509-547.

Jeong, G.M., H.S. Ahn, S.I. Choi, N. Kwak and C. Moon, 2010. Pattern recognition using feature feedback: Application to face recognition. Intern. J. Control Autom. Sys., 8: 141-148.

Olson, C.F., 1999. Constrained Hough transforms for curve detection. Comput. Vision Image Understanding, 73: 329-345.

Rao, M.S. and B.E. Reddy, 2011. Comparative analysis of pattern recognition methods: An overview. Indian J. Comput. Sci. Eng., 2: 385-390.

Willis, A. and Y. Sui, 2009. An algebraic model for fast corner detection. Proceedings of the 12th International Conference on Computer Vision, September 29-October 2, 2009, IEEE, Kyoto, pp: 2296-2302.