Adaptive Bayesian Recognition with Multiple Evidences

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***Abstract*— Ensuring robustness in object recognition/pose estimation under a wide variation of environmental parameters, such as illumination, scale, perspective as well as occlusion, is still of a challenge in computer vision. One way to meet this challenge is by using multiple features/evidences that offer their own strengths against particular environmental variations. To this end, methods of how to choose an optimal combination of features/evidences and of how to design an optimal classifier/decision-maker with the assignment of proper weights to the chosen individual features/evidences, for a given environmental parameter reading, are to be addressed. This paper presents a framework of adaptive Bayesian recognition that puts its particular emphasis on addressing the two methods described above while integrating multiple evidences. The novelty of the proposed method lies in 1) an AND/OR graph representation of evidence structure for individual object, representing explicitly a set of combined evidences sufficient for decision, and 2) An automatic update of the Bayesian network tables of conditional probabilities based on the current environmental parameters measured. The experimental results show that the proposed method is capable of dealing with adverse situations for which conventional methods fail to provide recognition.**

Keywords-component; Adaptive Bayesian Recognition, Multiple Features Extraction, Evidence Structure, Octree Segmentation, 3D Shape Descriptor, Color Appearance Vector, 3D SIFT, Pattern Recognition, Computer Vision

I. INTRODUCTION

In order to implement a reliable commercial service robot, it must have flexible, adaptive, and robust vision system that can identify and recognize objects in a very cluttered, unpredictable, and uncontrollable environment. For achieving such performance and robustness, a framework of several recognition features should be integrated. Proposing such a system would necessarily require a fusion model that combines these features for decision making. It would also require a learning/adaptation subsystem that updates fusion coefficients and confidences of each individual feature according to environmental changes. In this paper, we propose an adaptive object recognition system that probabilistically combines several features while adapting to variations in the surrounding environment. Proposed approach is being tested and used in the 3rd generation of our service robot, KORUS HomeMate [1], which is equipped with MS Kinect RGBD sensor, Bumblebee 2 stereo camera, as well as an onboard Intel Core i7 notebook. This robot has been deployed in several elderly care centers as a prototype for testing and evaluation proposes.

This paper is arranged as follows: Section II: related work, differences and originality of proposed approach are introduced. Section III: Adaptive Bayesian recognition framework is explained. Section III.A: We describe the segmentation of objects of interest to be investigated. Section III.B: a brief description of features, which are used to extract evidences, is provided. Section III.C: we describe Evidence Structure; our probabilistic Bayesian approach to combine evidences. Section III.D: the Self-Adaptation process is introduced. Section III.E, we briefly describe the computational model used to achieve real-time performance. Section IV: experimental results of proposed framework is presented. Section V: concludes this paper and our future works.

II. RELATED WORK

Individual recognition feature can provide impressive results under certain optimal environmental conditions. For example, Geometric-based features, such as BOR3D [2] can successfully recognize objects under sever luminance conditions, in which photometric features, such as MOPED [3], and SIFT [4] may fail. Photometric features, on the other hand, provide more discriminative results for similar shaped objects. Thus, in order to realize a reliable and robust recognition system that can successfully run under variable and/or severe environment conditions; integration of multiple features is important. Such integration requires probabilistic fusion as well as an adaptive process that updates fusion coefficients according to environmental changes. There were several attempts to combine multiple recognition features rather than just adapting one. In [5] and [6], fusion of 3D lines, SIFT, (and color in [5]) features were carried out by particle filter. In [7], a more feasible probabilistic model is used to fuse both positive and negative evidences of a single 3D lines feature by computing likelihood and unlikelihood. In [8], a Bayesian framework is introduced to determine the optimum feature to apply (out of 3 features: 3D lines, SIFT, and color). This selection is based on online environmental measurement referenced with statistical database described in [4]. This

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feature selection approach guaranteed high performance computation for a single pipeline model.

Modern approaches, like in [9] and [10], try to fuse several features while providing a scalability and robustness to the system. In [10], a probabilistic fusion approach was used to combine 3D model matcher; color; and OCR/bar code features. Results showed the advantage of fusing different features online. However, neither environment adaptation process nor computational model was discussed. In [9], meta-recognition, a score-based machine learning approach was used to fuse BOR3D, a point-cloud based feature; MOPED, a texture-based feature; and an HSV color-based feature respectively. The proposed approach provided scalability by relying on Support Vector Machine SVM classifier. Machine learning might outperform statistical-based approach in high dimensional nonlinear classifications, however, at the risk of over fitting and being stuck at local maxima. The author described the computational structure which ran all features separately, however, presented no means to adapt classifier to online environment variations.

Many of object recognition researches focus on improving the representation of objects, classification and overall performance of the system. However, there is a gap in researches dealing with online environmental variations to be expected in an unstructured open environment. We are presenting a novel approach for a highly robust adaptive recognition system fusing geometric-, photometric-, and texture-based features. Probabilistic Bayesian- based approach is used to fuse evidences, while an adaptive system is developed to update these coefficients according to environmental changes. We describe the computational model of our approach and show its experimental results in difficult situations.

III. PROPOSED ADAPTIVE BAYESIAN RECOGNITION FRAMEWORK

Proposed framework consists mainly of four main layers: 1) Candidate generation layer: we perform segmentation and represent candidates to be investigated. 2) Evidences' collections layer: multiple features are measured and matching probabilities are computed simultaneously. 3) Evidence structure layer: probabilities of multiple features are fused using Bayesian network. And 4) Self-Adaptation layer: parameters and data treatment changes according to environmental variations.

A. Segmentation of Objects of Interest

After RANSAC-based surface estimation and elimination of the context in which objects lie on, we were able to generate octree cells and segment scene objects; using octree representation approach described in [11]. This robust octree representation is broadcasted as the row input to our recognition features. Octree cell size is limited, however, according to memory size. It is important to adjust cell size according to the minimum geometric feature of interest of targeted object. In case of this optimum size is prohibited by memory size, an adaptive approach is introduced to optimize octree cell size as part of proposed Self-Adaptation process presented in Section III.D.V of this paper.

B. Feature Extraction for Evidences

The proposed framework combines evidences through a pre-defined evidence structure by Bayesian network. It is important to note that the framework is scalable and not limited to the features selected, as introduced in the following.

B.I. 3D Shape Descriptor

There are many approaches, such as BOR3D [2], which perform 3D geometric-based model matching. We have developed our own geometric-based 3D Shape Descriptor that takes advantages of our high-performance Octree representation introduced in Section III.A. Proposed approach extracts several invariant geometric features, such as object height, surface area, concavity ratio, top shape, body shape, circle index … etc and match them to a database of hyper ellipsoids of all target objects.

$$Likelihood\,(Object\,/\,measure) = \frac{1}{\sqrt{(2\pi)^k|\Sigma|}}\,e^{-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)}$$

$$\text{Probabilit iy(Object} = \text{T/measure)} =$$

$$= \frac{\text{P(measure/ Object} = \text{T)P(Object} = \text{T)}}{\text{P(measure)}}$$

$$= \frac{\text{P(measure/ Object)P(O bject} = \text{T)}}{\sum_{X=T,F}\text{P(measure/ Object} = \text{X)P(Object} = \text{X)}}$$

$$= \frac{1}{1+\dfrac{\text{P(measure/ Object} = \text{F)P(Object} = \text{F)}}{\text{P(measure/ Object} = \text{T)P(Object} = \text{T)}}} \qquad (1)$$

$$\text{P(Object} = \text{T)} = \text{P(Object} = \text{F)} = \text{marginal}$$

$$\text{Probabilit iy(Object/ measure)} =$$

$$= \frac{1}{1+\dfrac{\text{P(measurem ents/Objec t} = \text{F)}}{\text{P(measurem ents/Objec t} = \text{T)}}}$$

$$= \frac{1}{1+\dfrac{\arg\max_{i\neq r}\{\text{P(measurem ents/Objec t\# i} = \text{T)}\}}{\text{P(measurem ents/Objec t\# r} = \text{T)}}}$$

A threshold of likelihood set point is used to filter close candidates, and a probability is calculated according to false/true likelihood ratio as shown in (1) and Figure 1. The set of geometric features used to discriminate between database objects are defined as sufficient conditions and are used in Evidence Structure (Section III.C.)

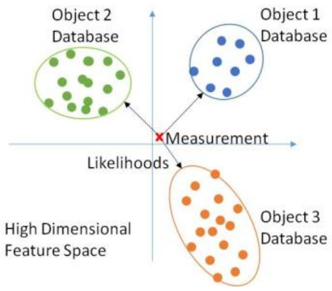

Figure 1. 3D Shape Descriptor Feature Space.

B.II.Color Appearance Vectors

Color-based recognition is not an easy task due to the variations in environmental intensity, light tune color, and object texture and material. In order to provide high reliability, we have developed a robust and flexible color-based classifier in Hue, Saturation, and Value (HSV) space. First, we define and separate chromatic and achromatic pixels in SV space (Figure 2). For achromatic pixels, we divide V space into black/gray/white areas and count the amount of pixels in each area using a fuzzy algorithm. Achromatic division is a function of average intensity of the scene.

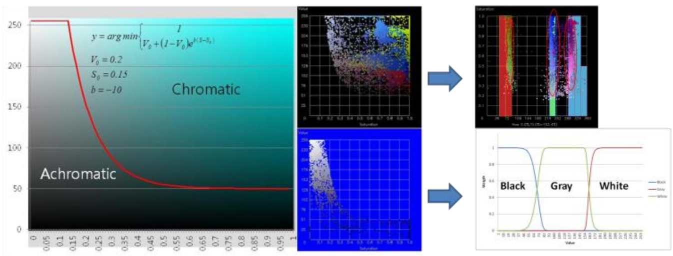

Figure 2. Color division and representation.

For chromatic pixels, we segment their peaks in HS space using a fast Quadtree algorithm and define 2D ellipsoids that cover each peak. For each ellipsoid, we extract 5 temporal features along with additional 2 spatial features and represent them as a point in 7D feature space. Similarly to shape descriptor matching described by equation (1), we match achromatic 3D point to the nearest object database ellipsoid using false/true likelihood ratio. We also match each of the chromatic peaks, in the same way, in 7D feature space. Final probability is computed using equation (2)

$$\text{Probability(Object\# r/measurements)} = \frac{1}{1+\dfrac{\arg\max_{i\neq r}\left\{\text{P(Ach/Object\# i\_Ach)}\prod_{j=1\sim n}\text{P(Ch}_j\text{/Object\# i\_Ch}_j)\right\}}{\text{P(Ach/Object\# r\_Ach)}\prod_{k=1\sim m}\text{P(Ch}_k\text{/Object\# r\_Ch}_k)}} \quad (2)$$

B.III. 3D SIFT

Inspired by reliability of work in [3], we have adapted SIFT as a texture-based recognition feature. SIFT, however, is a 2D feature extraction and matching framework.

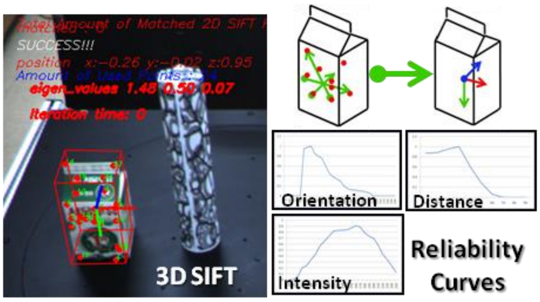

Figure 3. 3D SIFT example and reliability curves (provided at [13]).

So, we have developed our own framework that uses SIFT 2D matched points as a base candidate points for 3D matching. We remove outliers and calculate probability, by using sigmoid distribution as a function of the number of 3D matched points. Additionally, if there are sufficient number of matched 3D points, we use it to estimate 6DOF pose of the candidate (Figure 3). SIFT is variant to orientation and its performance drops dramatically for orientation difference of 30 degrees or more (according to statistics provided at [13]). Thus, we had built a database of 16 different orientations to cover all 360 degrees of all possible orientations.

C. Probabilistic recognition with Evidence Structure

There are many ways to fuse multiple evidences. Deterministic approaches like using a high dimensional classifier may not be feasible, because they require extremely large amount of training sample. Classifiers constructed by linearly representing training samples provide inaccurate results. Nonlinear classifiers, on the other hand, require high computational process. Probabilistic approaches, like Bayesian classifier, provide a more robust and reliable results as they are not affected by under sampled training dataset. Performance, however, is affected by heuristic knowledge embedded in system design. Choice of features, their reliability, fusion process, and decision boundary are all set offline.

We have chosen to adapt Evidence Structure, a Bayesian based probabilistic model to describe relevant evidences for recognition of an object as well as the proper method of fusion. The novelty of this paper is by relying on statistical knowledge acquired from training samples, instead of heuristic knowledge for setting Bayesian priori probabilities as well as updating them according to environmental measurements. First, let's define two types of operations that are allowed to propagate probability through Bayesian network as in (3)

$$\begin{aligned}
P(f_1 \text{ OR } f_2) &= \text{argmax}\{\, P(f_1=\text{T}),\, P(f_2=\text{T})\,\} \\
P(f_1 \text{ AND } f_2) &= a.P(f_1=\text{T}).P(f_2=\text{T}) + \\
&\quad b.P(f_1=\text{T}).P(f_2=\text{F}) + \\
&\quad c.P(f_1=\text{F}).P(f_2=\text{T}) + \\
&\quad d.P(f_1=\text{F}).P(f_2=\text{F})
\end{aligned} \quad (3)$$

Where a, b, c, and d are Bayesian conditional probabilities representing features' priori reliabilities. These priori probabilities are determined initially from training dataset, stored in Bayesian Table format, and updated online using environmental parameters as shown in Section III.D.III. Using this notion, we define Sufficient Condition (Figure 4) as a set of features which are sufficient to discriminate an object from other objects in system database. An object can now be modeled as a set of sufficient conditions. Probability of an object can then be calculated as in (4)

$$\begin{aligned} P(Object / measurement) &= P(Object / OR_{i=1}^{n} \text{sufficient}_i) \\ &= \mathrm{P}\left(\text{Object} / OR_{i=1}^{n}\left(AND_{j=1}^{m_i} f_j\right)\right) \end{aligned} \tag{4}$$

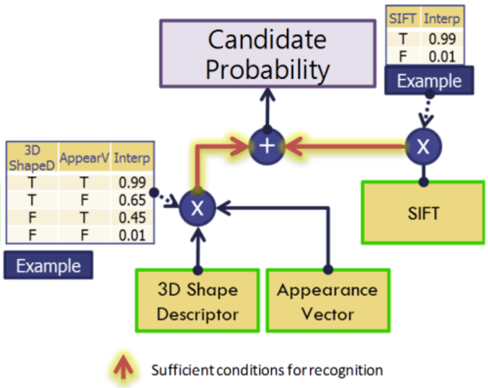

Figure 4. Sample evidence structure of a textured and shaped object.

D. *Self-Adaptation to Environmental Variations*

Regardless of the discriminative ability and performance, any feature will not produce reliable results if applied under non-optimal conditions. Since we aim to construct a robust recognition framework that performs evenly well under any conditions; especially in low-light, cluttered, and occluded indoor environment, it is necessary to apply environmental adaptation process. We propose a Self-Adaptation process that consists of 5 components:

D.I. Measurement of Environmental parameters

Using our high-performance octree-cell-based segmentation, we can robustly measure environmental parameters for each candidate. We project each candidate into image frame of each sensor and measure 4 main parameters: intensity level, intensity histogram distribution, distance, orientation, and occlusion rate.

D.III. Bayesian Network update

By using statistical analysis shown in [13], we can estimate the reliability of each individual feature (Figure 5) from the environmental parameters measured in previous component.

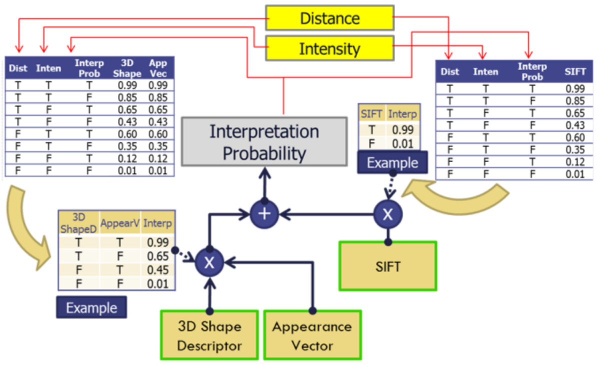

Figure 5. Process of updating Bayesian tables.

Let Bayesian table and statistical analysis table of a single feature be as in Table 1. Updating Bayesian table is performed using the above statistical table, environmental measurement parameters, and prior probability of the feature as in (7)

TABLE I. BAYESIAN TABLE (LEFT), AND STATISTICAL TABLE (RIGHT) OF A SINGLE FEATURE

Probability of feature	*Probability of object / probability of feature*	
	True	*False*
True	A	1-A
False	B	1-B

Probability of object	*Probability of feature / probability of object*	
	True	*False*
True	a	1-a
False	b	1-b

$$\begin{aligned} A &= \frac{P(O_p = T, O_d = T)}{P(O_d = T, O_p = \{T, F\})} \\ &= \frac{P(O_d = T / O_p = T)P(O_p = T)}{P(O_d = T / O_p = T)P(O_p = T) + P(O_d = T / O_p = F)P(O_p = F)} \\ &= \frac{aP(O_p = T)}{aP(O_p = T) + b[1 - P(O_p = T)]} \end{aligned} \tag{5}$$

$$similar,$$

$$B = \frac{(1-a)P(O_p = T)}{(1-a)P(O_p = T) + (1-b)[1 - P(O_p = T)]}$$

D.IV. Fusion of weak evidences

This is the core advantage of the proposed framework. When different evidences from various features are high but not strong enough for convergence; fusion of these evidences –for the same candidate– would provide a reasonable strong result. This fusion is not only carried out on probabilistic part of the algorithm, but also is carried out on the resulting pose of each evidence as well.

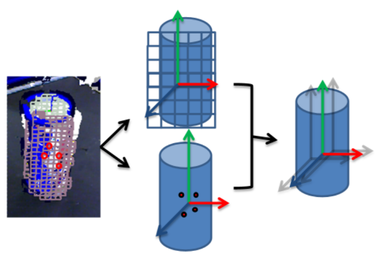

Figure 6. Fusion of 3D Shape descriptor, and SIFT poses.

For example, when SIFT matched 3D points are not sufficient for convergence and/or stable pose estimation; and if these matched points lies in the candidate region that has high 3D shape descriptor matching probability; a fusion of both evidences would provide higher probability. And by linearly combining SIFT pose with 3D shape descriptor pose, resulting pose becomes accurate estimation of the (Figure 6).

D.V. Enhancing accuracy of geometric measurements

As described in Section III.B, we are using a geometrical-based feature, 3D Shape Descriptor, which relies on octree-cell representation of scene candidates. Draw-back of the high-performance octree representation is its memory constraints.

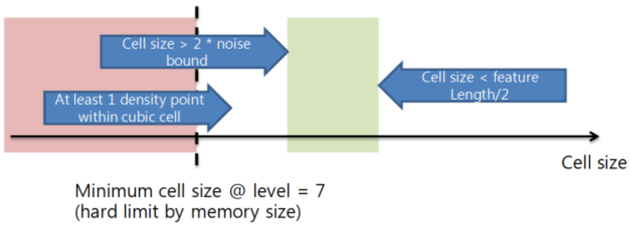

Figure 7. Constraints on determining optimum octree cell-size.

Thus, a hard limit on the amount of octree cells that can be generated at one scene poses a limitation on geometric measurement accuracy. We defined optimum octree cell size required to accurately measure and extract geometrical features of target object. This optimum size is bounded by the memory hard limit (mentioned above) as well as other 3 constraints as shown in Figure 7.

$$
\begin{aligned}
& P_{noise} < threshold \\
& P_{noise} = \int_{r=0}^{h_{error}} \left[\frac{1}{L} \left(\frac{h_{error} - r}{2h_{error}} \right) \right]^n dr \\
& = \left(\frac{1}{2h_{error} L} \right)^n \int_{r=0}^{h_{error}} \left[(h_{error} - r) \right]^n dr \\
& = \left(\frac{1}{2h_{error} L} \right)^n \left. \frac{(h_{error} - r)^{n+1}}{n+1} \right|_{h_{error}}^{0} \\
& = \left(\frac{1}{2h_{error} L} \right)^n \left[\frac{(h_{error})^{n+1} - (h_{error} - h_{error})^{n+1}}{n+1} \right] \\
& = \frac{h_{error}}{(n+1)(2L)^n} \\
& @\, n = 3: \\
& = \frac{h_{error}}{32L^3} < threshold \\
& L_1 > \sqrt[3]{\frac{dpth_{error} Sin(tilt)}{32.threshold}}
\end{aligned} \qquad (6)
$$

The first constraint guarantees that effect of depth error on geometrical measurement is bounded with a threshold. Figure 8 and equation (8) demonstrate how to calculate this bound. Constraint 2 and 3 guarantee that the cell size is large enough so that every nonempty space provides enough point density to generate a cell at this particular distance, while being small enough to stably recognize minimum object geometrical feature. They are calculated in equation (9)

$$
\begin{aligned}
& L_2 \geq \frac{2.a.\text{Distance.T an}(\frac{\text{FOV}}{2})}{\text{Resolution}} \\
& L_3 \leq \frac{\min imum\_length.\text{Resolution}}{2.a.b.\text{Distance}.Tan(\frac{FOV}{2})}
\end{aligned} \qquad (7)
$$

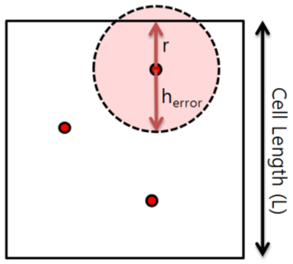

Figure 8. Probability of point cloud depth error to validate a false cell.

First and second constraint are easy bounds. They normally do not pose hard limit within relevant distances. On the other hand, third constraint is often hard to achieve due to the memory size limit. Memory constraint limits the number of cells that can be generated at once, not cell size. Thus, in order to further reduce cell size and allow first constraint to be met, smaller volume of interest is required in which octree is generated for.

Our proposed adaptation process has the advantage of prior generated probability of candidates to determine which candidate is worth more investigation. During the recognition, if probabilities generated for such candidates are not sufficient for convergence, Self-Adaptation process takes a corrective action by adjusting octree generator to generate cells with optimum cell size for each of these candidates sequentially. This allows 3D Shape Descriptor to acquire more measurements of the geometric features of the candidates, thus, enhancing the chance to successfully match the target object.

IV. EXPERIMENTAL RESULTS

The proposed recognition framework is being used in our KORUS HomeMate 3rd generation, a service robot that is running as a prototype in elderly care center in Seoul to help elders in their day to day activity in the center.

A. Performance Capabilities Demonstration

For comparison and demonstration purposes of this paper, we have conducted five recognition experiments of various objects in various environments. The results are compared with a non-adaptive framework and a framework that relies on one feature (MOPED2 open source code [3]).

A.I. Experiment 1: Highly Cluttered Environment

An object (apple yoghurt box) is located in an environment full of other obstacles (Figure 9). Recognition system was able to find the object using photometric feature. Number of 3D matched SIFT points was twelve.

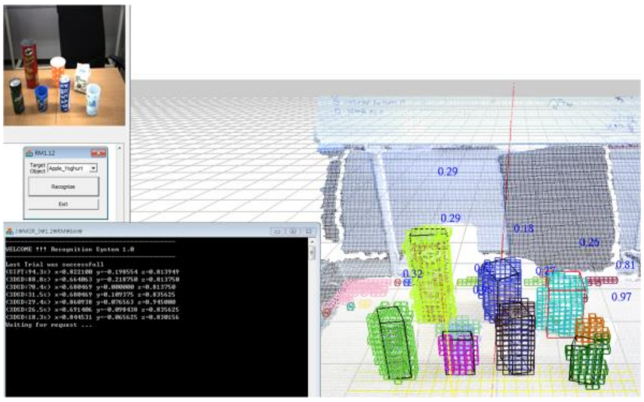

Figure 9. Experiment 1: Recognition in highly cluttered environment.

A.II.Experiment 2: Completely Dark Environment

An object (flags-textured cup) is located in a cluttered and completely dark environment (Figure 10). Self-Adaptation process reduced Bayesian coefficient of photometric features and recognition was done using 3D Shape Descriptor which relies only on geometric representation of the candidates measured by IR of the sensor. MOPED2 failed due to the improper illumination.

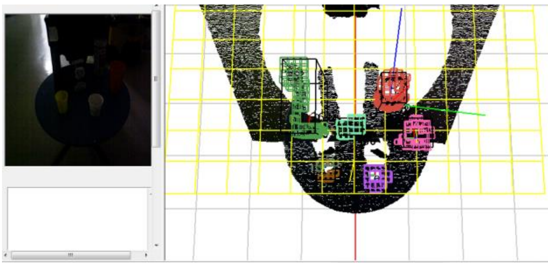

Figure 10. Experiment 2: Recognition in completely dark environment.

A.III. Experiment 3: Recognizing Texture-less Cup

An object (yellow plastic texture-less cup) is placed in a cluttered environment (Figure 11). Object evidence structure only consists of geometric features. Thus, only 3D Shape Descriptor and color Appearance Vectors are applied. Recognition was successful through the collection of color, aspect and concave evidences in spite of partial occlusion. MOPED2 is not applicable for non-textured object

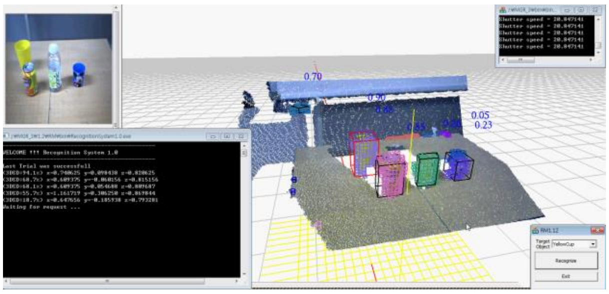

Figure 11. Experiment 3: Recognition of texture-less object.

A.IV. Experiment 4: Partial occlusion case

An object (apple yoghurt box) is located behind an obstacle. Target object is suffering from partial occlusion and cannot be fully seen by the sensors (Figure 12). Photometric feature (SIFT) was not successful due to the insufficient number of 3D matched points (6 points). 3D Shape Descriptor also failed to match the object due to the incorrect of measured aspect ratios. However, Self-adaptation process found out that the matched 6 SIFT points lie on the surface of the highest 3D shape descriptor candidate. So, it fused both features results and was able to, not only successfully detect the object, but also determine an accurate estimation of its pose.

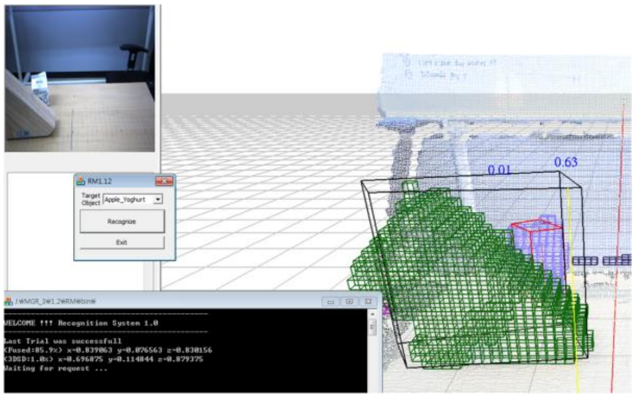

Figure 12. Experiment 4: Recognition of partially occluded object.

A.V.Experiment 5: Severe occlusion case

An object (Pringle potato chips box) is located behind a tall and large obstacle (Figure 13). Target object is suffering from severe case of occlusion and only less than 20% of its volume is visible.

Photometric features failed to recognize the object due to the lack of surface area exposure to the sensors. 3D shape descriptor, however, was able to locate the object as the exposed volume was sufficient for aspect ratio extraction. Also, a strong geometric feature was recognized (convex/concave feature of the object). This boosted the recognition probability to exceed the required criteria for convergence; thus, framework was finally successful in recognizing the target object. MOPED2 failed due to the lack of texture exposure.

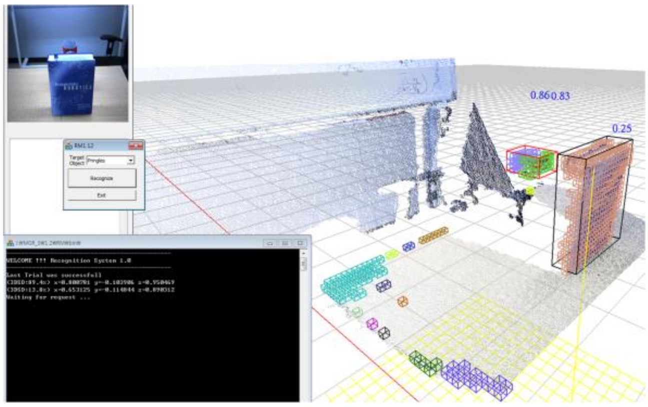

Figure 13. Experiment 5: Recognition of severely occluded object.

B. Performance Statistics

An Xtion PRO camera is placed 1.2cm above the ground, 50cm away from a 4800cm2 table. 10 objects are scattered on top of the table. The whole setup and experiment is described and recorded in [15]. One hundred recognition cycles were executed (10 cycle per object). Figure 14 shows the recognition performance.

Overall, out of 100, there were no misclassified objects (false positive = 0%). However, the system failed eight times to recognize the target object (false negative = 8%). Average recognition time was 359.8ms.

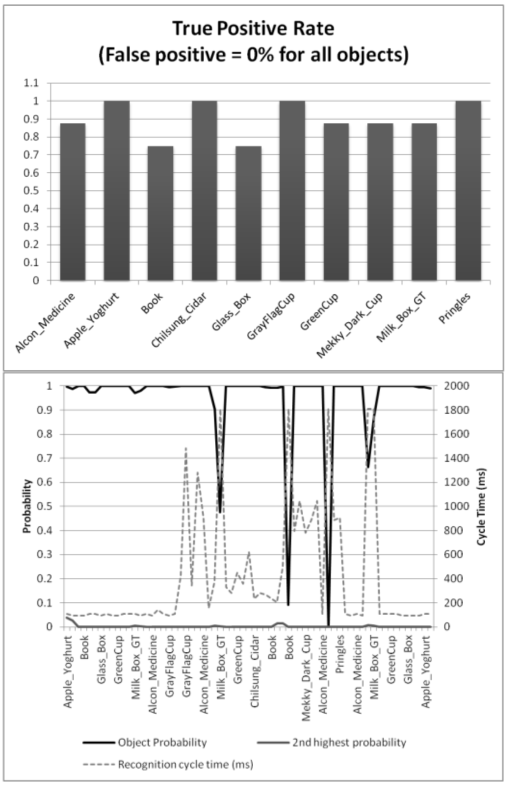

Figure 14. True/False Positive for 10 objects (left) and Discrimination capabilities of experiments as well as processing time (right).

V. CONCLUSIONS

Experimental results prove the proposed recognition framework to be robust, flexible and efficient. It was shown that the introduction of Self-Adaptation process resulted in an improved overall performance that surpasses the sum of each individual feature performance. Finally, proposed framework is also being tested in real open environment; we used prototype robot in real elderly care centers. Feedback shows reliability of recognition framework performance.

Future work involves integration of other features, increase of framework structure modularity as well as development of online statistical database creation through the integration of machine learning.

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