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Guiding a Robotic Gripper by Visual Feedback for Object Manipulation Tasks

Rigas Kouskouridas
Department of Production and Management Engineering
Democritus Univeristy of Thrace
Xanthi, Greece GR-67100
Email: rkouskou@pme.duth.gr

Angelos Amanatiadis
Department of Production and Management Engineering
Democritus Univeristy of Thrace
Xanthi, Greece GR-67100
Email: aamanat@ee.duth.gr

Antonios Gasteratos
Department of Production and Management Engineering
Democritus Univeristy of Thrace
Xanthi, Greece GR-67100
Email: agaster@pme.duth.gr

***Abstract*—This paper presents a novel object manipulation technique that could be adopted by any advanced mechatronic platform in order to perform demanding pick and place tasks. The ultimate goal of a robotics researcher is to provide an applicable manipulation solution that minimizes user's involvement. It has been shown that the best solution to this problem is provided by the introduction of sensors that allow an automatic or, at least, semi-automatic grasping of the targets. The proposed method relies on a vision-based framework that is responsible for several vital tasks that affect directly the manipulation process. The contribution of the paper incorporates a shape retrieval technique accompanied with classification and clustering algorithms that are utilized during the objects' pose estimation process. The experimental results obtained confirm the validity of the presented approach.**

I. Introduction

The current trend in mechanical and electronic engineering is the building of more sophisticated mechatronic systems excelling in simplicity, reliability and versatility. Moreover, the intricacy nature of their parts require integrated control systems accompanied with advanced visual feedback. Generally, in the last few years, the ultimate goal of robotics researchers is the construction of autonomous vehicles that can substitute humans in time demanding tasks. To this end, industries put efforts on developing machines capable of assisting people in everyday life. Among all the operations realized by human beings, the majority is directly related to object manipulation either for eating/drinking (i.e., grasping the spoon or the cup) or for handling an object. In the literature four main streams for the adequate accomplishment of object manipulation tasks by autonomous vehicles are distinguished [1].

Workstation systems are usually comprised of a robotic arm mainly fixed to a desk whilst, the grasping process is position-based and requires perfect knowledge of the environment. The main drawback of such systems constitute the fact that they are able to manipulate a restricted set of objects. The most popular systems of this first category of assistance robots are the Master [2], MySpoon [3], HANDY 1 [4] and PROVAR [5]. On the other hand, *stand alone manipulators* aim at avoiding the knowledge of environment by incorporating sensor feedback within the control loop. Usually, a system of this category is lighter than a *workstation* but the working space of the robotic arm remains restricted due to the fact that it is mounted onto a fixed structure. This category is based on platitudinous technology resulting in the building of the Tou [6] and ISAC [7] frameworks. In turn, *wheel chair mounted systems* emphasize in increasing the working space of the robotic arm by installing it on a wheelchair. Systems of this category may comprise of several sensor for automating control processes. Cameras appear to be the most used technology since they provided the majority of the information available. Furthermore, the most popular schemes of this stream are the Manus, Raptor [8], FRIEND II [9] and the VICTORIA project [10]. The most advanced assistive robots belong to the category of *mobile platforms,* where the robotic arm is mounted onto an autonomous vehicle. The latter is equipped either with laser sensors [11], [12] or cameras [13], [14] in order to adequately fulfill demanding navigation tasks. In this category dominate the systems of the SAM robotic butler [15], the KARES-II project [16] and the CARE-O-BOT 2 [12].

Another issue that has received attention in the literature, is how to reduce the user's involvement in an object manipulation process. It has been shown that the best solution to this problem is provided by introducing sensors that allow an automatic or, at least, semi-automatic grasping of the targets. Visual feedback from the respective sensors enhance system's versatility and autonomy since the latter enjoys several visual attributes such as the perception of depth needed for object manipulation. Generally, a vision system aims at bridging the gap between humans and machines in terms of providing to the latter information of what is visually perceived. In an object manipulation process, a vision framework must pledge vital data concerning the target's pose (i.e., rotation and translation) relative to a specific coordinate system [17], [18], [19]. The task of estimating the pose of an object involves the determination of the correlation between extracted features in 2D images and their correspondences in the 3D space. One of the most widely used image feature that is exploited in either pose estimation or image retrieval systems is shape. Moreover, recently in [20], a method that aims at finding, attending, recognizing and manipulating objects in domestic environments is presented. It encompass a stereo-based vision system framework as opposed to our system that utilizes

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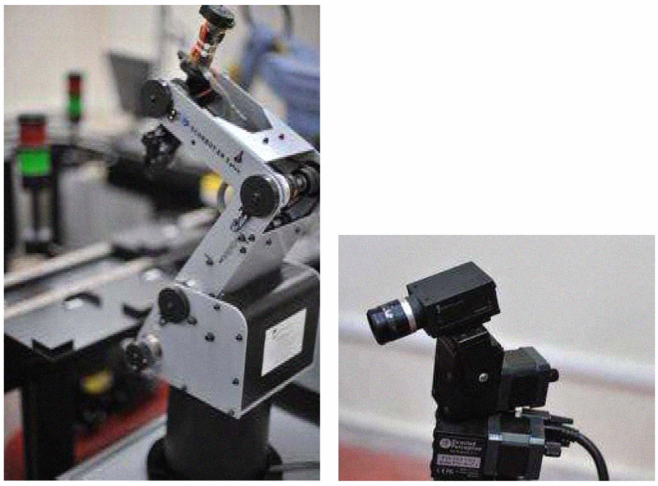
monocular vision techniques.

In this paper we present a novel manipulation technique that is based on visual feedback obtained through a standard vision framework. The proposed system is able to classify objects according to their shape since it incorporates an enhanced database and sophisticated shape invariant descriptors. Apart from manipulation, information extracted via the vision system could be utilized in navigation and obstacle avoidance tasks whilst the grasping of objects is based on the novel depth estimation technique presented in [21]. The remainder of the paper is structured as follows: In Section II, the overall architecture of the vision-based object manipulation framework is presented in detail. In Section III, we emphasize in the vision-based object grasping along with the shape retrieval framework that provides several important information utilized during the objects' pose estimation process. The proposed system was evaluated through a series of experimental sets whilst, the outcome of them is presented in Section IV. Finally, the future work and some final notes are drawn in Section V.



(a) (b)

Fig. 1. a) The SCROBOT-ER Vplus robotic arm and b) the Grasshopper camera mounted onto the pan-tilt mechanism.

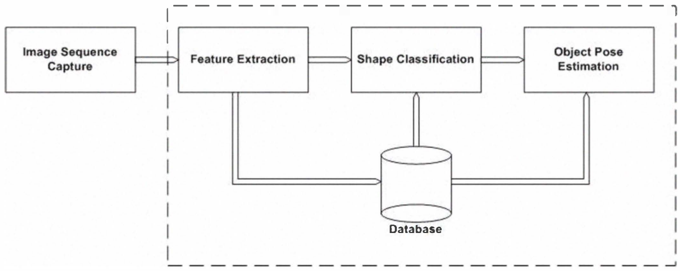


Fig. 2. The block diagram of the proposed object manipulation technique

II. System Architecture

The technique presented in this paper is mainly based on two components, the robotic arm and the camera. The latter is mounted on the PTU(46-17.5) pan-tilt mechanism manufactured by Directed Perception [22], whilst both of them lay on top of the robotic arm. Is is apparent that, the proposed method could be adopted by any advanced mechatronic scheme that aims at reducing user's participation in manipulation tasks.

A. Robotic Arm

The robotic arm utilized is the SCORBOT-ER Vplus depicted in Figure 1(a) and manufactured by Intelitek [23], which is a vertical articulated robot, with five re-volute joints. With gripper attached, the robot has six degrees of freedom. This design permits the end effector to be positioned and oriented within a large work space. The length of the links and the degree of rotation of the joints determine the robot's work envelope. The location and movement of each axis is measured by an electro-optical encoder attached to the shaft of the motor which drives the axis. When the robot axis moves, the encoder generates a series of alternating high and low electrical signals. The number of signals is proportional to the amount of axis motion. The sequence of the signals indicates the direction of movement. The controller reads these signals and determines the extent and direction of axis movement.

B. Vision Sensor

The camera used is the Grasshopper vision framework 1(b) manufactured by PointGrey [24] and is able to capture images up to 1280 x 960 pixels resolution, whilst being connected to the PC via the firewire port. Moreover, the data transmission is accomplished by using the IEEE 1394b transfer protocol.

III. Vision-based Object Manipulation

In this section we will analytically present the main components of the proposed vision-based object manipulation technique. The key idea underlying our method is illustrated in Figure 2. As it could be easily apprehended the proposed method is based on three major processes. The first one corresponds to the system preparation and to the building of the database that contains information exploited in later stages of the method. The second procedure represents a novel technique for shape retrieval from visual cues and a new clustering algorithm that classifies new inputs into the respective categories. The last process includes the estimation of the pose of the object that is a prerequisite in an object manipulation process. This routine utilizes information derived through the retrieval/classification algorithms and already contained in the database whilst, adopting a novel object depth calculation method that utilizes features' scatter over the surface of the objects. Initially, the proposed method extracts the shape of the object - target and as a next step, classifies the object into the corresponding categories. As a result, the object is now characterized by several spatial attributes that are located into the database and are exploited during the pose estimation process. During the latter, the proposed method estimates objects' distance from the camera by simply calculating the features' distribution over the targets' surface.

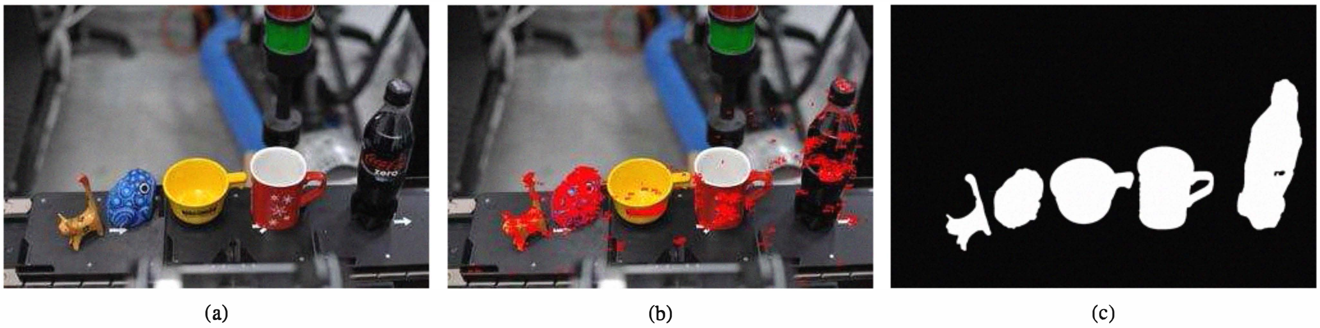


Fig. 3. a) The initial scene as captured through the left camera of the Bumblebee. b) The extracted features of each object and c) The binary image is given as an input at the shape classification procedure.

A. System Preparation and Database Construction

This stage of the method could be apprehended as the training session of the proposed framework where the system remains off-line and several objects - targets are separately shot. The database is divided into two pats where, the first one corresponds to data needed during recognition and pose estimation process. In the second part of the database several object categories based on the shape are accumulated. Each category of the database contains information concerning the manipulation in the following form $[R_x, R_y, R_z, d]^k$, where R_x, R_y and R_z represent the rotation of the griper in the respective axis, d corresponds to the opening percentage of the gripper and k to the number of the object category. In other words, each category is characterized by several vital attributes that are effectively exploited during the pose estimation process. Several possible objects - targets may belong to the same class (i.e., Cup) but it is unlike to belong to the same instance (i.e., Cup type A with $R_x = R_y = R_z = 0$ and $d = 7$). We have enriched the proposed system by utilizing large scale databases containing several rigid and non-rigid, texture and texture-less objects. Moreover, for the shape retrieval and classification process we used a unified database based on two widely used binary shape datasets. The first dataset is the MPEG-7 data set for the Core Experiment CE-Shape-1, part B, illustrated in [25]. All the 1.400 image data set divided in 70 shape classes of 20 images each where used in our database. This set has been reported as a very useful set for testing similarity-based retrieval and the shape descriptor's robustness to various arbitrary shape distortions. The second database is the ETH-80 database [26] which contains 80 objects from eight categories. For each object, there are 41 images from different viewpoints.

B. Shape Retrieval and Classification

The challenging task of this subsystem is the accurate extraction and representation of shape information. The extraction of shape descriptors is even more complicated when invariance, with respect to a number of possible transformations, such as scaling, shifting, and rotation, is required [27]. We used a complementary scheme of three different shape descriptors for achieving the best accuracy in shape representation [28]. More precisely, we used Fourier descriptors [29], which are contour-based descriptors since they are extracted from the contour, and both affine moment invariants [30] and angular radial transform descriptors [31] which are region-based since they are extracted from the whole shape region.

The indexing process for each descriptor was performed based on their optimal number of coefficients from the current literature. More specifically for Fourier descriptors we used the first 32 descriptors, for the angular radial transform the first 35 descriptors and the 6 affine moment invariants.

For classification we used a Fuzzy Lattice Reasoning (FLR) scheme as outlined in a preliminary work [32]. More specifically, a 2-D shape was represented by three populations of three different shape descriptors $d \in FD, ART, IM$, respectively, such that one population was represented by one Intervals' Number (IN) as detailed in [33], [34].

A FLRtypeII scheme for learning (training) was applied followed by a FLRtypeII scheme for generalization (testing) on the benchmark data set. If an unknown object which is not in the training set, is introduced in the scene, a classification based on the smallest class distance is realized.

C. Pose Estimation

The module described here enables to move the arm just in front of the object with a view to the efficient accomplishment of the grasping process. The efficiency of a manipulation task is directly related to the process of estimating the pose of the target. A pose estimation task aims at calculating an object's orientation and translation relative to a specific coordinate system. In computer vision, matched features from 2D images are combined in order to estimate the 3D model of an object, whilst the whole process could be apprehended as an advanced feature correspondence maximization problem. Generally, the pose of the target i with respect to the camera's frame is:

$$M_i = \begin{bmatrix} R_i^{3x3} & T_i^{3x1} \\ 0 & 1 \end{bmatrix}$$

where R_i^{3x3} and T_i^{3x1} represent the rotation (i.e., 3x3) and translation (i.e., 3x1) matrices of object i relative to camera's frame. After the shape classification process we obtain the rotation matrix R corresponding to the respective object - target i. The translation matrix T is calculated using the method presented in [21] where, during the database

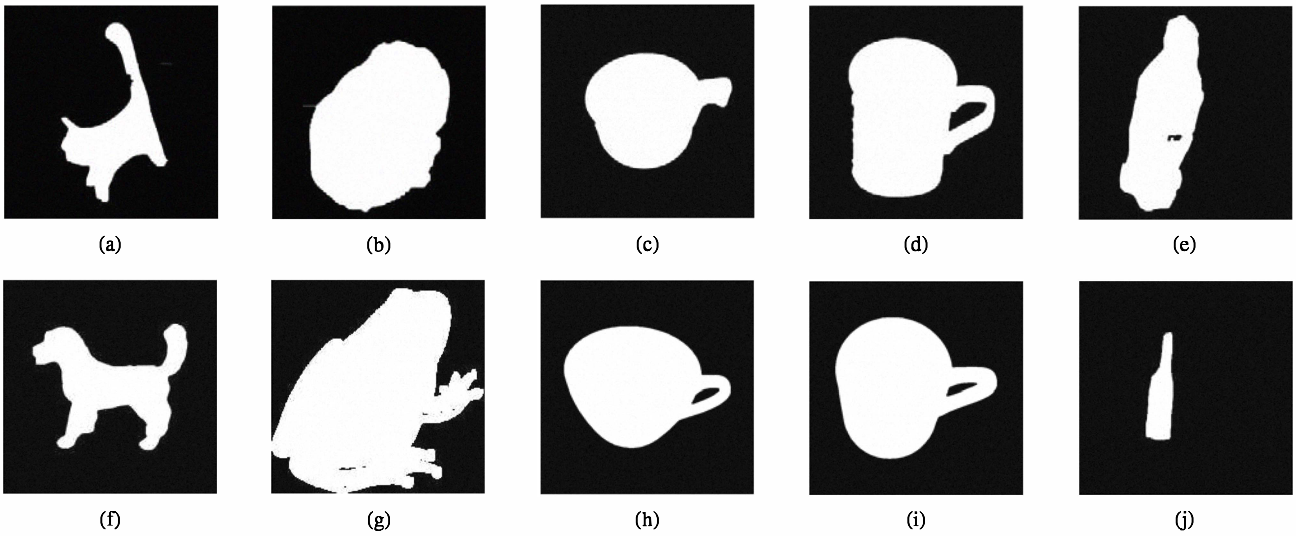


Fig. 4. Classification results: (a)-(e) The query images; (f)-(j) the retrieved images from MPEG 7 CE-Shape-1 and ETH 80 databases.

construction images of each object are captured at different distances from the camera and the measured depth d_O is stored. The ultimate goal is to estimate objects' distance from the camera (Z^*) by taking into account the spatial information obtained during training. Thus, considering a given features' distribution over the object's surface corresponding to a known depth, object's distance from the camera, in cases where the distribution alters, can be computed. The further an object is positioned from the camera the denser the distribution of its features becomes, and this relation is linear. As far as feature extraction is concerned, the proposed method adopts any two-part (i.e., implements both a detector and a descriptor) object recognition framework such as SIFT [35] and SURF [36].

Once we obtain the transformation matrix T, the next step is to transmit to the manipulator data concerning the location of the objects' in the scene. Since we hold data concerning the camera's pose relative to the manipulator, the final pose of the object is calculated by simple multiplying the extracted object's pose matrix to the transformation matrix P, where

$$P = \begin{bmatrix} I^{3x3} & T_i^{3x1} \\ 0 & 1 \end{bmatrix}$$

IV. Experimental Results

The proposed object manipulation process that is based on visual feedback is evaluated through extended tests containing several scenes and objects. As far as the vision part of the process is concerned, the tests were executed on a typical PC with a core2duo 2.2 GHz processor, 2 GB RAM and Windows XP operating system. The process starts with the extraction of features from the image sequences being captured by the camera. In Figure 3, five different objects positioned in front of the gripper are illustrated. This scene contains namely the objects $-four\ legged\ animal-$, $-frog-$, $-cupA-$, $-cupB-$ and $-bottle-$.

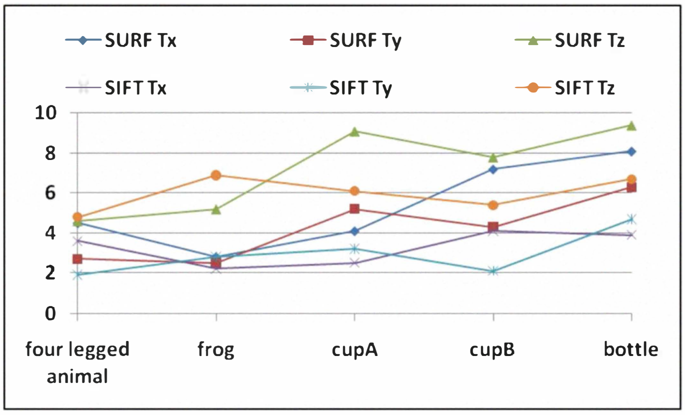


Fig. 5. The estimated mean error in cm concerning the translations of the five objects of scene 3 for the three axis.

Our first goal was to correctly identify the classes of the objects in the scene. This was achieved through the classification process using the algorithm and databases that we have previously presented. The results are shown in Figure 4. The first row presents the extracted shapes that were used as query images. The second row presents the first retrieved result for each shape respectively using both shape databases concurrently. From the results we can understand that apart from the right classification accuracy, we achieved also a good orientation matching. This would lead to better accuracy in the pose estimation process.

After the efficient accomplishment of the classification task the system continues with the estimation of the objects' pose. As mentioned in Section III-C, the rotation matrix of the object - target is calculated by exploiting the spatial information contained in the database. In more detail, each instance of an object class is accompanied with information of the form $[R_x, R_y, R_z, d]^k$, where R_x, R_y and R_z represent the rotation

TABLE I
THE EFFICIENCY OF THE PROPOSED POSE ESTIMATION METHOD FOR THE FIVE OBJECTS OF SCENE 3 WHEN ADOPTING EITHER SIFT OR SURF.

		SIFT		SURF	
object id	**groundtruth (T_X, T_Y, T_Z)**	**mean error (cm)**	**std error**	**mean error (cm)**	**std error**
-four legged animal-	(-19.4, -8.8, 49.4)	(3.6, 1.9, 4.8)	2.48	(4.5, 2.7, 4.6)	5.14
-frog-	(-13.8, -4.2, 52.7)	(2.2, 2.8, 6.9)	3.17	(2.8, 2.5, 5.2)	4.67
-cupA-	(-7.4, -6.9, 49.6)	(2.5, 3.2, 6.1)	2.28	(4.1, 5.2, 9.1)	2.57
-cupB-	(6.8, -7.2, 48.2)	(4.1, 2.1, 5.4)	4.41	(7.2, 4.3, 7.8)	4.32
-bottle-	(16.4, 1.7, 47.9)	(3.9, 4.7, 6.7)	6.65	(8.1, 6.3, 9.4)	8.29

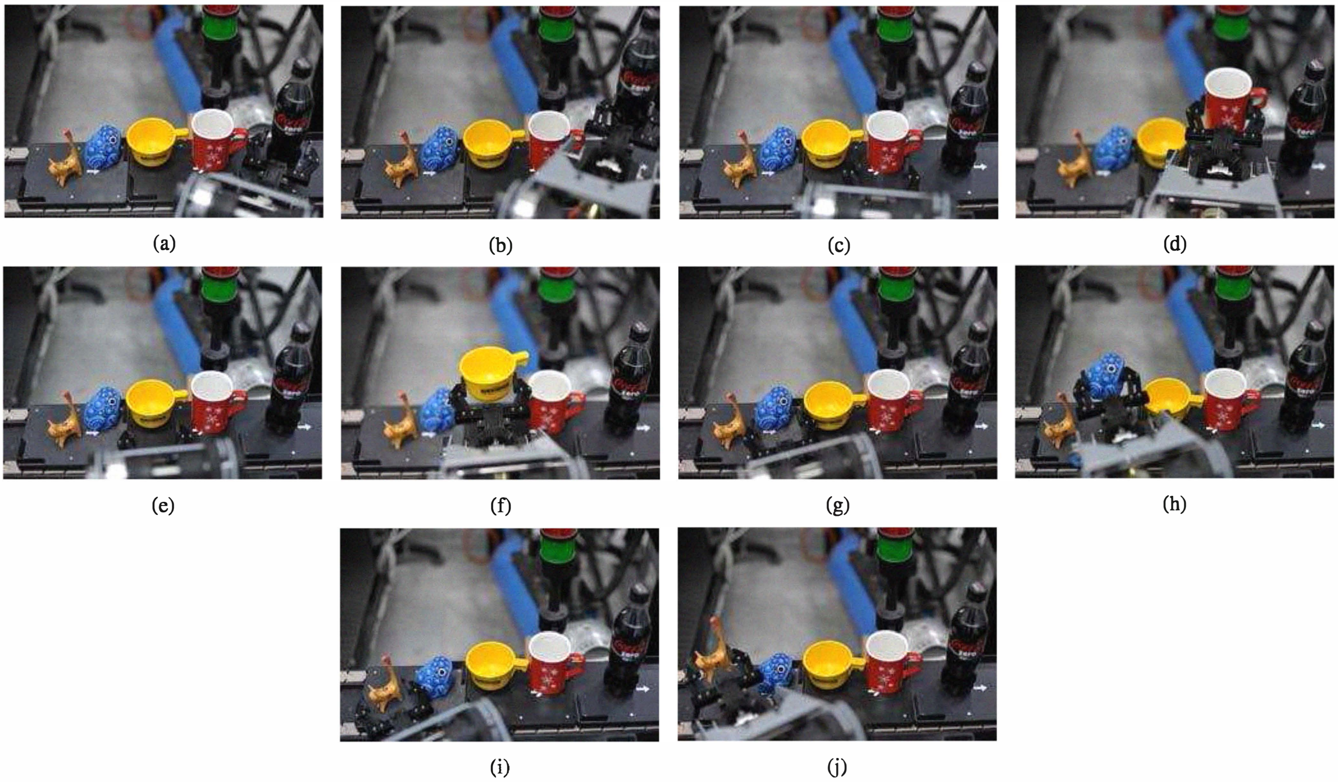


Fig. 6. The grasping process for the (a)-(b) $-bottle-$, (c)-(d) $-cupB-$, (e)-(f) $-cupA-$, (g)-(h) $-frog-$ and (i)-(j) $-four\ legged\ animal-$, respectively, as they are shown in Figure 3.

of the griper in the respective axis, d corresponds to the opening percentage of the gripper and k to the number of the object class. It is apparent that, in order to fulfill the pose estimation task, the information concerning the translation of the objects in the respective axes is needed. The latter is computed by adopting the method presented in [21] for object depth estimation and by taking into account information derived through camera calibration. Especially, we consider the camera's frame as the reference coordinate system, whilst all the measurements are based on the principal point of the camera as calculated through calibration. In Table I, the comparative results of the proposed pose estimation technique while using either SIFT of SURF are presented. As it can be seen, by adopting any of the aforementioned methods, the proposed method is able to assign pose to any textured target with remarkable efficiency. In Figure 5, the oscillation of the mean estimated error for the translations along the three axes concerning the five objects in cases of adopting either SIFT or SURF is presented. The final outcome of the proposed module is presented in Figure 6 where the five objects are grasped by the manipulator.

V. CONCLUSION

In this paper a novel visual feedback technique that is able to guide a robotic gripper in object manipulation tasks has been presented. The proposed method is characterized by its novelty, simplicity and computational cost, whilst it is able to adequately prepare an object manipulator for demanding pick and place tasks. Our method relies on a sophisticated shape classification technique that allows the categorization of unknown objects into several classes contained in the system's database. The latter contains spatial information that is given as an input at the object's pose estimation procedure. For the efficient calculation of the targets' orientation relative to the camera's frame we have used a recently presented algorithm that is able to remarkably estimate objects' distance from the sensor. The key idea behind the position estimation method is the fact that, considering a given features' distribution over the object's surface corresponding to a known depth, object's distance from the camera, in cases where the distribution alters, can be computed. The proposed method was tested through a series of experimental setups containing several objects with different arrangements, whilst the results denote the validity of our method. This system represents the starting point of a new series of research activities that will lead to the integration of advanced mechatronic platforms. The mounting of the gripper and the camera onto an autonomous vehicle will represent a new advanced robotic system able to navigate freely in the interior workspace of an indoor environment and capable of executing manipulation tasks.

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