GRASP CONFIGURATION MATCHING
Using Visual and Tactile Sensor Information

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Abstract: Finding the global shape of a grasped object directly from touch is time consuming and not highly reliable. This paper describes the relationship between visual features and grasp planning, and correlates visual and tactile information for a better description of the object's shape and grasping points determination. The grasping process proposed is experimented with a three fingered robotic hand.

1 INTRODUCTION

Grasping has been an active area of robotics research in the last decades. Although a great number of sensory systems have been used to monitor and to control grasping, their usefulness is often limited by the ability of handling all aspects of detection/recognition, guidance, alignment and grasping. To place our approach in perspective, we review existing methods for sensor based grasp planning. The existing literature can be broadly classified into two categories; vision based and tactile based. For both categories, the extracted image features are of concern, they can range from geometric primitives such as edges, lines, vertices, and circles to optical flow estimates. The first category uses image features to estimate the robot's motion with respect to the object pose (Maekawa et al., 1995), (Smith and Papanikolopoulos, 1996), (Allen et al., 1999). Once the robot hands is already aligned with the object, then, it only needs to know where the fingers are placed on the object. The second category of sensor uses image features to estimate the touch sensing area in contact with the object (Berger and Khosla, 1991), (Chen et al., 1995), (Lee and Nicholls, 1999). A practical drawback is that the grasp execution is hardly reactive to sensing errors such as finger positioning errors. A vision sensor, meanwhile, is unable to handle occlusions. Since an object is grasped according to its CAD model (Kragic et al., 2001), an image also contains redundant information that could become a source of errors and inefficient in the processing.

This paper is an extension of our previous work (Boudaba et al., 2005) and (Boudaba and Casals, 2006) on grasp planning using visual features. In this work, we demonstrate its utility in the context of grasp (or fingers) positioning. Consider the problem of selecting and executing a grasp. In most tasks, one can expect various uncertainties. Grasping an object implies building a relationship between the robot hand and the object model. The latter is often unavailable or poorly known. Thus, selecting a grasp position from such model can be unprecise or unpracticable in real time applications. In our approach, we avoid using any object model and instead we work directly from edge features. In order to avoid fingers positioning errors, a sizable image blocks are defined that represent the features of grasping contact points. This not only avoids detection/localization errors but also saves computation effort that could affect the reliability of the system. Our features matching based approach can play the critical role of forcing the fingers to move to the desired positions before the task of grasping is executed. To achieve a high level of matching efficiency, the visual image is first divided into squared blocks of pixels. Then for each one of these blocks the algorithm tries to find its correspondence in the target block that is the closest

to it according to a predetermined criterion. Finally, we reduce or eliminate redundant information contained in the image by transforming the result of the matching algorithm to the frequency domain. Then a compression scheme is proposed to the image coding.

The proposed work is divided into two phases:

1. **Grasp planning phase:** For each two-dimensional view of an object in a visual frame features of its contour are calculated. These features are then used as input data, both for the grasp planning and features matching phases. The grasping positions are generated in the planning task, so a relationship between visual features and grasp planning is proposed. Then a set of geometrical functions is analysed to find a feasible solution for grasping. The result of grasp planning is a database containing a set of valid grasps, the most favorable as well as those rejected.
2. **Sensor features matching phase:** Unlike vision which provides global features of the object, tactile sensor provides local features when the fingertip is in touch with the object. In order to identify and locate the features that best fit the two domains (vision and touch) of features, a contour splitting process divides the object's contour into blocks, so that different matching techniques can be applied. For the purpose of features matching, extracting edge features are of concern using the basic results from different approaches. The matching is conducted in two-dimensional space. Each edge in the block is treated as features.

2 GRASP BACKGROUND

Geometric formulation and grasp feasibility are reviewed and discussed based on (Hirai, 2002). Given a grasp which is characterized by a set of contact points and the associated contact models, the problem is determining whether the grasp has a force-closure. For finger contact, a commonly used model is point contact with friction (PCWF). In this model, fingers can exert any force pointing into the friction cone at the edge of contacts (We use edge contact instead of point contact, which can be described as a linear combination of two vectors, see Figure 1(b)). To fully analyze grasp feasibility, we need to examine the full space of forces acting on the object. Forming the convex hull of this space is difficult due to the nonlinear friction cone constraints imposed by the contact models. In this section, we only focus in precision grasps, where only the fingertips are in contact with the object. After discussing the friction cone modeling, a formalizme is used to analyze force closure grasps using the theory of polyhedral convex cones.

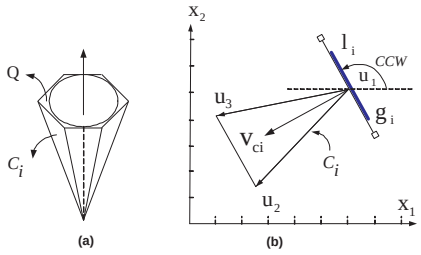


Figure 1: Friction cone modelleing.

2.1 Friction Cone Modelling

For the analysis of the contact forces in planar grasps, we simplify the problem by linearizing the friction cone by a polyhedral convex cone. In the plane, a cone has the appareance shown in Figure 1(b). This means that we can reduce the number of cone sides, m=6 to one face.

Let's denote by P, the convex polytopes of a face cone, and $\{u_1, u_2, u_3\}$ its three representative vertices. We can define such polytopes by

$$P = \left\{ x = \sum_{i=1}^{3} \delta_i u_i : 0 \leq \delta_i \leq 1, \sum_{i=1}^{3} \delta_i = 1 \right\} \quad (1)$$

2.2 Grasp Space Evaluation

The full space of a grasp is evaluated by analysing its convex hull. For a set of friction cone intersections, the full space can be defined by

$$C_1^k = C(P_1) \cap C(P_2) \cap C(P_k) \quad (2)$$

where k is the number of grasping contacts. Note that the result of C_1^k is a set of friction cone intersections and produces either an empty set or a bounded convex polytope. Therefore, the solution of (2) can be expressed in terms of its extreme vertices

$$\Omega_1^{v_p}(U) = \left\{ \sum_{i=1}^{v_p} \alpha_i u_{ci}, \quad \sum_{i=1}^{v_p} \alpha_i = 1, \quad \alpha_i \geq 0 \right\} \quad (3)$$

where v_p is the total number of extreme vertices.

Figure 2 illustrates an example of feasible solution of $\Omega_1^{v_p}(U)$ and its grasp space represented by its extreme vertices $P = \{v_1, v_2, ..., v_5\}$.

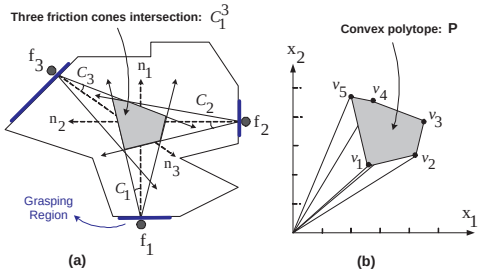


Figure 2: Feasible solution of a three-fingered grasp.

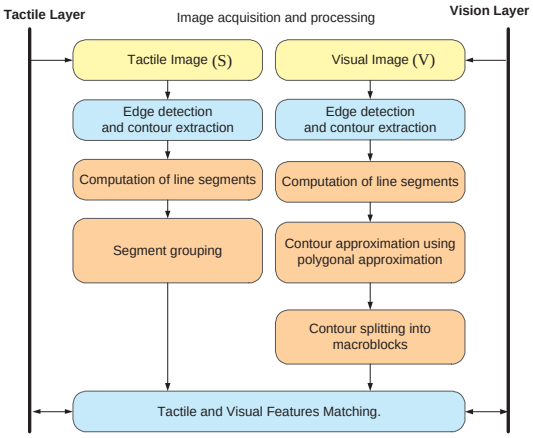


Figure 3: Tactile and visual features data processing.

3 FEATURES-BASED GRASPING

In robotic grasping tasks, when several input sensors are available simultaneously, it is generally necessary to precisely analyze all the data along the entire grasping task. We can acquire the precise position and orientation of the target object and robot hand motion from a vision system and can acquire force, torque, and touch information from tactile sensing. The object being extracted from a video sequence requires encoding its contour individually in a layered manner and provide at the receiver's side an enhanced accessibility of visual information. In the same way, for the object being extracted from a tactile sensor, the tactile layer processes and provides the tactile information at its receiver's side. Obviously, the accuracy of this data is of significant importance for the eventual matching algorithm.

Figure 3 illustrates a layered composition of a tactile and a vision sensor. Given as input two consecutive images data S (tactile) and V (visual), the success (or simply the completion time) of the task depends on the level of processing efficiency.

3.1 Visual Features Extraction

Due to their semantically rich nature, contours are one of the most commonly used shape descriptors, and various methods for representing the contours of 2D objects have been proposed in the literature (Costa and Cesar, 2001). Extracting meaningful features from digital curves, finding lines or segments in an image is highly significant in grasping applications. Most of the available methods are variations of the dominant point detection algorithms (M. Marji, 2003). The advantage of using dominant points is that both, high data compression and feature extraction can be achieved. Other works prefer the method of polygonal approximation using linking and merging algorithms (Rosin, 1997) and curvature scale space (CSS).

We denote by V a function regrouping parameters of visual features defined by

$$V = \{vlist, slist, llist, com\} \quad (4)$$

where *vlist* and *slist* are the lists of consecutive contour's vertices and segments, respectively. *llist* is a list containing the parameters of segments, calculated with respect to the object's center of mass, *com*. The resulting parameters of V fully describe the two-dimensional location of features with respect to the image plane. The visual features obtained can be used as input data for both, grasp planning and features matching for grasp control.

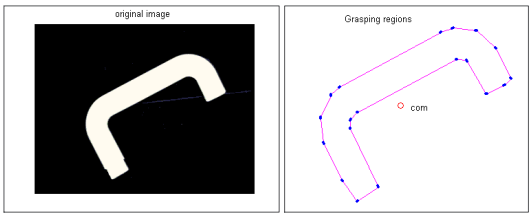


Figure 4: Visual features extraction.

3.2 Tactile Features Extraction

Unlike vision which provides global features of the object, tactile sensor provides local features when the fingertip is in touch with the object. To simplify the problem, tactile features are treated as visual features using the basic results from different approaches (Lee

and Nicholls, 1999). For the purpose of sensor features matching, extracting edge features are of interest. Figure 5 illustrates three examples of tactile sensor in touch with the object. From left to right side, the sensitive area is shown with hashed region and located at upper corner side, bottom side and covering the entire object area, respectively. The tactile sensor device consists of a printed circuit board with a tactile array of electrodes (called tactels) on its surface and circuitry to deliver the tactile data of local features extracted from the sensing elements, as well as circuity to monitor and adjust the power supply voltage to the sensor. The raw data from the sensing elements is processed and produces as output a vector S containing the parameters that define tactile features.

$$S = \{elist, slist, plist\} \tag{5}$$

where *elist* and *slist* are list of consecutive contour edges and segments, respectively. *plist* is a list containing the parameters tied to segments, such as location and orientation in the tactile sensor plane.

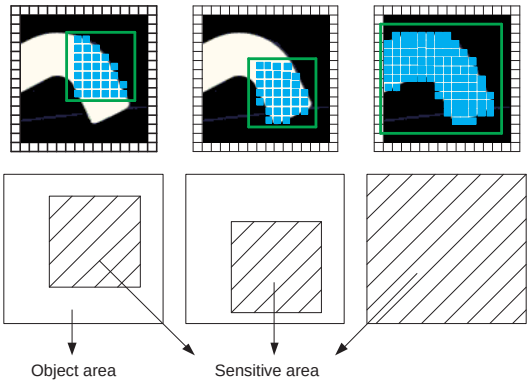


Figure 5: Sensitive area of the tactile sensor. This information can be determined by examination of the frequency domain, and is shown in Figure 10.

4 GRASP PLANNING

Grasp planning can be seen as constructing procedures for placing point contacts on the surface of a given object to achieve force-closure grasps. Taking as input the set of visual features extracted from the contour of the object, the output is a set of valid grasps. The relationship between visual features and grasp planning is given in the next section.

4.1 Grasp Point Generation

Generating a number of valid grasps from a list of candidates and classifying the best among them is quite time consuming. Thus a preprocessing (or prefiltering) is necessary before the grasping points generation takes place. A fingertip is estimated to be as a sphere with radius f_r (see Figure. 2(b)), a grasping region must be large enough for placing contact points on it. Hence, a prefiltering is applied to the list, *slist* defined in (4) to discard those segments with length less than the diameter of the sphere ($s_i < 2f_r$). Figure. 4 illustrates the result of prefiltering processes as described by the following equation:

$$glist = \{g_1, g_2, \cdots, g_m\} \tag{6}$$

where *glist* is a linked list of grasping regions and m its number.

A very important aspect of (6) is the way how knowledge about grasping regions are represented in the extraction process, knowledge that will be used for generating grasping points.

The following equation describes the relationship between the visual features and grasp planning

$$G = f(glist, gparam, com) \tag{7}$$

where *glist*, *gparam*, and *com* are the visual features observed on the image plane and G is a grasp map of outputs defined by the relationship between fingers and the location of contact points on its corresponding grasping regions. From the grasp map G three possible solutions are derived:

$$G : \begin{cases} G_s = \{G_{s_1}, G_{s_2}, \cdots, G_{s_{is}}\} \\ G_b = \{G_{b_1}, G_{b_2}, \cdots, G_{b_{ib}}\} \\ G_r = \{G_{r_1}, G_{r_2}, \cdots, G_{r_{ir}}\} \end{cases} \tag{8}$$

where G_s, G_b, and G_r are selected, best, and rejected grasp, respectively. The *is*, *ib*, and *ir* are the number of selected, best, and rejected grasps, respectively.

For a three-finger grasps, the selected grasps (G_s) are given in the following form:

$$G_s : \begin{cases} G_{s_1} = \{(f_1, g_1), (f_2, g_6), (f_3, g_9)\} \\ G_{s_2} = \{(f_1, g_2), (f_2, g_6), (f_3, g_{10})\} \\ \vdots \\ G_{s_{is}} = \{(f_1, g_1), (f_2, g_8), (f_3, g_{12})\} \end{cases}$$

where f_i and g_i are the $i-th$ finger and grasping region, respectively.

A similar form can be given for representing the best grasps G_b and those rejected G_r.

4.2 Algorithm

The grasp planning algorithm is divided into several procedures and operates as follows:

1. *Visual features procedure*
   - *Function grouping visual features using (4)*
2. *Grasping point generation procedure*
   - *Pick three grasp regions from (6)*
   - *Determine the initial position of f_1, f_2 and f_3*
   - *Compute their friction cones using (1)*
   - *Compute the friction cones intersection of (2)*
3. *Grasping test procedure*
   - *Compute the solution friction cones using (3)*
   - *Check whether the polytopes given by (3) is bounded. If so, stop and save the selected grasps to G_s.*
   - *Else save the rejected grasps to G_r.*
4. *Quality test procedure*
   - *The last step of the algorithm consists of selecting the best grasps from a range of valid grasps from lower to upper acceptance measures by using the parameters measure given in table 1. Save to G_b.*

5 FEATURES MATCHING

Our goal is to match the grasping positions correspondence between the visual and tactile sensor features. The matching process works first getting a grasping position within its searching area and next it updates the tactile features using a tactile sensor. The size of the search windows is very important when configuring a matching process. The larger the search window, the longer it takes to process the search. The matching is conducted in the pixel domain, so the contrast is necessary for identifying edges in reference (visual) and target (tactile) image. Images with weak contrast should be avoided since the matching algorithm uses the edges based searching. The weaker the contrast, the less the amount and accuracy of edge-based information with which the searching is performed. Figure 7 shows two tables in grayscale values assigned to each block of matching.

5.1 Image Subregions

In order to identify the location of the best fitting between the tactile sensor frames and visual frames, a subregion process is performed that scales down the contour image into subregions in an efficient way so that the matching algorithm can be applied. The basic principle is similar to the image (or video) compression techniques, which defines how the component (RGB, YUV or YCrCb) can be down-sampled and digitalised to form discrete pixels. The terms 4:2:2 and 4:2:0 are often used to describe the sampling structure of the digital image. 4:2:2 means the chrominance is horizontally sub-sampled by a factor of two relative to the luminance; 4:2:0 means the chrominance is horizontally and vertically sub-sampled by a factor of two relative to the luminance. In the case of a 704x576 PAL/SECAM standard for example, the QCIF (Quarter Common Immediate Format) can be obtained by scaling down the image with a factor of 4 in the horizontal/vertical direction. For a QCIF format of size 176x144, there are 25.344 pixels in the frame. A macro block defines a 16x16 pixel area (256 pixels), so there are 99 macro blocks to process (see Figure. 6).

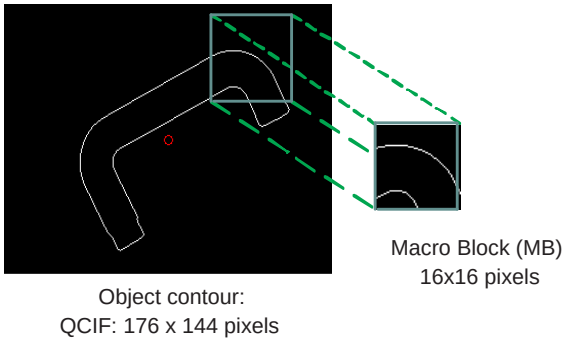


Figure 6: Image subregions.

5.2 Block-Matching Algorithm

The Mean Absolute Difference (MAD) is a well known matching criteria and widely used due to its lower computational complexity (Lu and Liou, 1997). Given two blocks represented by two set of features: $S = \{a_1, a_2, ..., a_q\}$ and $V = \{b_1, b_2, ..., b_q\}$, the corresponding features from each block are compared and their differences accumulated, as described by equation

$$MAD(dx, dy) = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} |V[i, j] - S[i + dx, j + dy]| \quad (9)$$

where $S(i, j)$ represents a $(N \times N)$ macroblock of pixel intensity in the target frame and $V(i, j)$ represents $(N \times N)$ macroblock of pixel intensity in the reference frame. (dx, dy) is a vector representing the

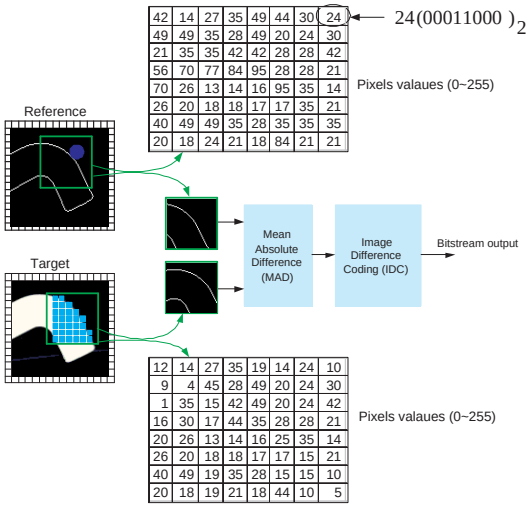


Figure 7: Block matching algorithm.

search area. For our application the search area is specified by $dx = (-p, p)$ and $dy = (-p, p)$ where $p = 6$ and $N = 16$.

The matching of a macroblock with another is based on the output of a cost function (9). The macroblock that results in the least cost is the one that matches the closest to current macroblock, Figure 7. For each fingertip that gets in touch with the object, the tactile features are matched to those of visual features inside a predefined searching area. A motion vector is then applied to search the features correspondence between blocks in the target frame and those in the reference frame. Figure 8 illustrates the searching method that evaluates the MAD cost function within the search area. Many other search methods can be found in (Furht, 1995).

5.3 Image Difference Coding

In order to control the grasping position, the result of the matching algorithm can be defined as error position or that so called error grasp, is then calculated using the following expression:

$$G_e(i, j) = V(i, j) - S(i + dx, j + dy) \qquad (10)$$

Since we want to guide the robot hand towards these grasping references G_{ref}, the solution consists of reducing the grasp error G_e by moving the tactile sensors towards the set of corresponding positions of grasping references. The cost of a solution is expressed as the total sum of contact displacements over the surface of the object from an initial contact configuration. If the result of matching is outside a given margin, then the grasp controller should launch a new measurement via joint angle and position

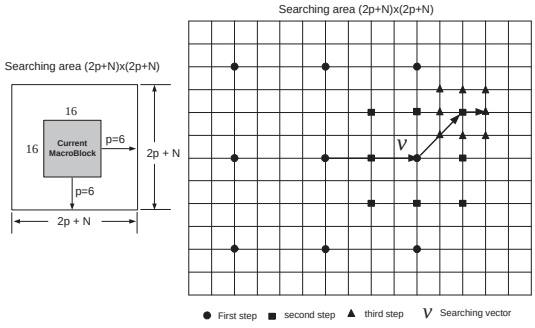


Figure 8: Searching area.

sensors.

The result of block matching algorithm (see Figure 8) is a two-dimensional vector called motion vector, $v(l, m)$. The Image Difference Coding (IDC) processes these measurements and produces as output a vector image containing the parameters of grasping positions, which are compressed in a suitable format to reduce the data transmission bandwidth. The digital cosine transform (DCT) is used due to its capability of removing spatial redundancy to achieve low bit rates.

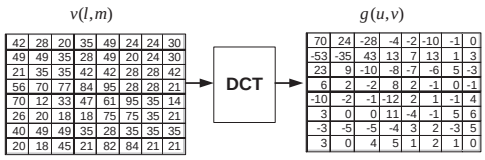


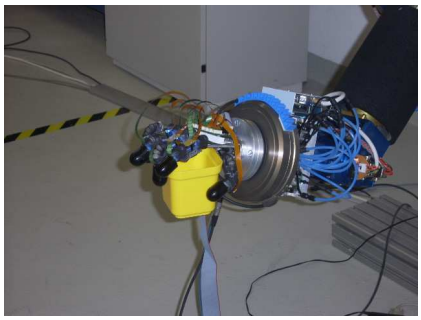
Figure 9: DCT Image compression.

The DCT transforms each 8x8 block of greyscale values into a block of 8x8 spectral frequency coefficients. The energy tends to be concentrated into few significant coefficients. Other coefficients are close to zero and insignificant (see Figure 9).
Next step of IDC is to compress the frequency domain, by not transmitting (or not coding) the close-zero coefficient (insignificant coefficients) and by quantizing and coding the remaining coefficients.

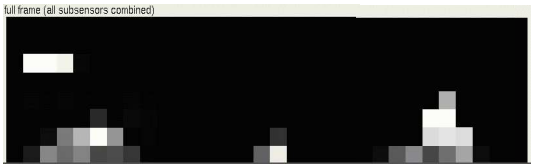
6 EXPERIMENTAL RESULTS

Figure 10 illustrates our experimental system which consists of a anthropomorphic robot hand equipped with a tactile array sensor on each fingertip and a stereo vision system. The spacial resolution of the tactile sensor has 256 (16x16) sensing cells over an area of 100 square millimeter. The sensory data processing were performed using MCAGUI and SVS tools for tactile and vision data, respectively, devel-

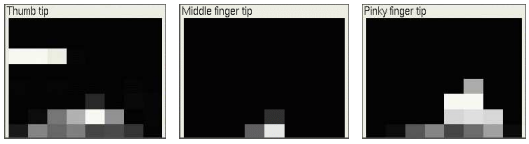
oped at the Institute of Process Control and Robotics (Boudaba et al., 2005). Figure 10(b) shows the tactile sensor response frames. Every cell of the sensing matrix is sampled at 10 frames per second. Figure 11 and Figure 12 show the result of five grasp configurations and Table 1 resumes their parameter measures. d_1, d_2 and d_3 are distance measures of finger position f_1, f_2 and f_3 from the object's center of mass. x_1 x_2 are the coordinates of the focus point F in the plane. d is the measured distance between focus point and center of mass. R is the vector radius of the ball centered at F. The object center of mass is located at $com = (121.000, 98.000$. The angle of the friction cone, $\alpha = 17.000$ for all configurations. We have implemented the grasp planning algorithms in Matlab environment for computing feasible grasping regions for three-finger hands.



(a) Three fingers hand in contact with the object



(b1) Full frame



(b2) Individual frame

Figure 10: Tactile sensor response frames.

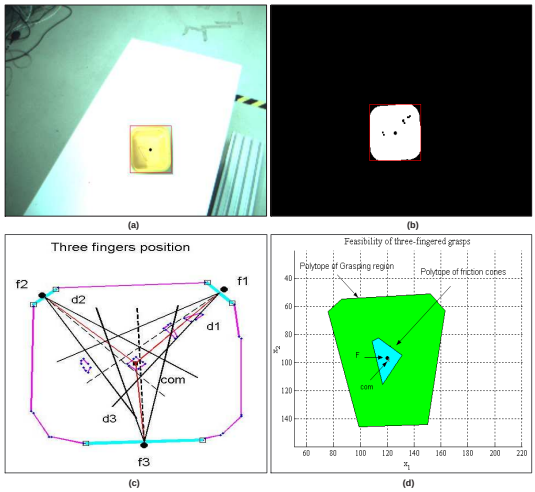


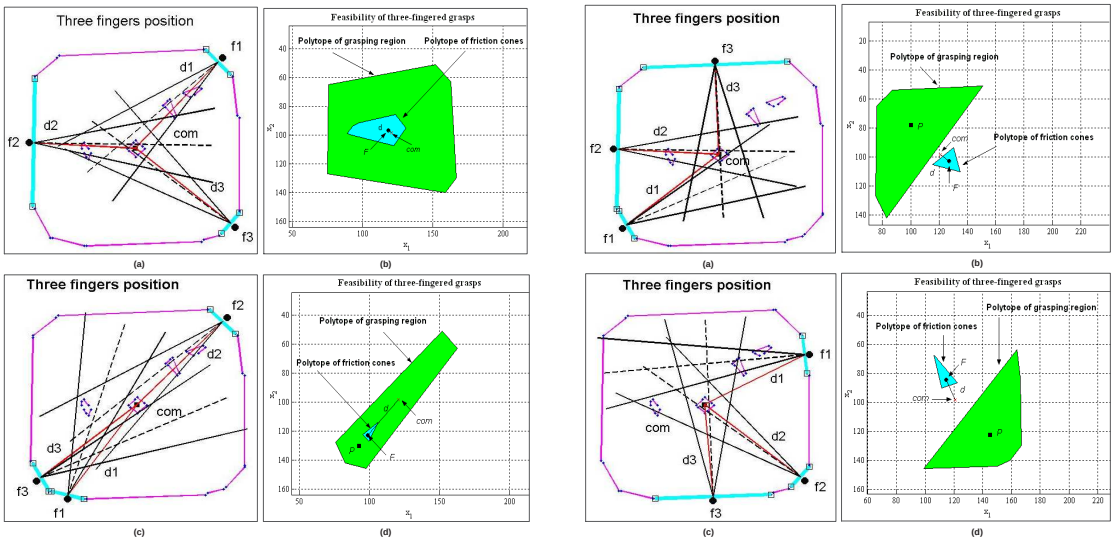
Figure 11: Grasp planning setup.

Table 1: Parameter measures of five grasp configurations.

$obj = \{GC1, GC2, GC3, GC4, GC5\}$			
d_1 d_2 d_3	$F(x_1, x_2)$	d	R
86.80 63.70 35.52	119.97 96.95	1.80	7.94
86.80 33.82 65.99	118.41 96.69	2.98	9.37
24.47 86.80 23.82	99.19 122.88	32.53	2.44
23.82 33.82 71.22	127.26 102.97	7.88	5.34
81.51 65.99 35.52	114.59 84.46	15.39	4.49

7 CONCLUSION

A framework to discuss sensor frames matching using tactile and visual features is presented in this paper. As a new approach to the grasp planning problem, the idea of vision-based grasping has been explored, within the specific context of using visual features relevant to the grasping and manipulation tasks, as complementary information to tactile data. In order to provide a suitable description of object contour, a method for grouping visual features has been proposed. Then a function defining the relationship between visual features and grasp planning has been described. A very important aspect of this method is the way knowledge about grasping regions are represented in the extraction process, which excluded all undesirable grasping points (unstable points) and all line segments that do not fit to the fingertip position. This filtering process has been used to reduce the time consumption during the process of determining suitable grasping points. For extracting the local features of the curves representing the object contour, the solution adopted is a polygonal approximation using a linking/merging algorithms.Then the force-closure condition is applied to evaluate grasping points determination. The method implemented here is currently restricted to any kind of 2D objects. In a future work, it is intended to extend our method to 3D object.The object therefore needs to be seen from different points of view which is desirable for grasp planning that performs well in the real world.



(a) Grasp Configuration(GC): 2-3 (b) Grasp Configuration(GC): 4-5

Figure 12: Result of Grasp planning with three-fingered Grasps.

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