Representation framework of perceived object softness characteristics for active robotic hand exploration

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1. INTRODUCTION

During the last years the principles and demands guiding the design and implementation of robotic platforms are changing. Nowadays, robotic platforms are tendency equipped with a conjugation of multi-modal artificial perception systems (stereo vision, tactile sensing) and complex actuation systems (multi-articulated robotic hands, arms and legs). This artificial perception systems are required by robotic systems to navigate and interact with the environment and persons. This work is focused in the artificial perception systems related with the robotic manipulation strategies used to dexterously interact with deformable objects in the environment.

In this context, the robotic dexterous manipulation of objects require that the framework used to represent the characteristics of the deformable manipulated objects should be suitable to receive inputs from multiple exploratory elements (multi-fingered robotic hands) and to progressively update that representation status as long as the exploration progresses on time. The framework should be also designed to incorporate the uncertainty and errors associated to the sensing process in this type of dynamic environments, and to deal with novelty by characterizing objects of new softness characteristics to the system based on the previous knowledge and interactions with a restricted set of reference materials, that constitute the haptic memory of the system.

In order to provide to the robotic hands the capability to differentiate deformable objects with distinct softness characteristics and to dexterously manipulate them, this work analyse the principles and strategies used by humans to sucessfully perform such type of tasks, using predominately haptic information. During the object exploration, the perception and discrimination capability of softness characteristics depend on both cutaneous and kinesthetic information by executing press and release movements [2] - active haptic perception. This has been demonstrated by psychophysical experiments performed by Srinivasan and Lamotte [5].

This work intends to contribute to the development of autonomous dexterous robotic hands platforms by proposing a probabilistic volumetric framework to represent and discriminate the perceived softness characteristics extracted during the exploration of deformable objects. The main contributions of this work are the model used to represent the perceived interaction signature of the active exploratory elements and the reference materials with different softness characteristics; the methods used to update the perceived softness volumetric representation of the explored object (Integration and fusion of the cutaneous and kinesthetic data, integration of the local context information).

2. PERCEIVED SOFTNESS MODEL OF THE REFERENCE MATERIALS

In this work the softness characteristics of each volumetric element of a manipulated deformable object (new to the system) are described as a probabilistic combination of M reference materials behaviour previously known - haptic memory concept. Analogously to [4], in this work, the specific contact interaction signature of each of the $m \in \{Material_1, ..., Material_M\}$ reference materials will be described by the following models:

$$C_P^m(C_D) = a_1^m C_D^{\frac{3}{2}} + a_2^m \qquad C_P^m(C_A) = a_3^m C_A^{\frac{3}{2}} + a_4^m \quad (1)$$

Let C_P be the resultant of the contact force intensity between the exploratory element and a material surface. The contact area of the exploratory element surface involved in the contact is designated by C_A. Let also denote by C_D the displacement of exploratory element beyond the natural surface of the material when the material surface is pressed. The softness characteristic signature of the active dynamic exploration of a material m is described in terms of the profile built from several data points of the format $\mathbf{M}_i = (C_{P,i}; C_{A,i}; C_{D,i})$, acquired during the training sessions. The profile represented by the set of data points $(C_{P,i}; C_{A,i}; C_{D,i})$ encodes the relevant information about the softness of the reference material, integrating the kinesthetic component represented by the relation $C_P(C_D)$ and integrating the cutaneous component represented by the relation $C_P(C_A)$.

For each of the reference materials, the constant parameters of the model, $\mathbf{a}_m = (a_1^m, a_2^m, a_3^m, a_4^m)$, are estimated using the Maximum Likelihood Estimation (MLE) method. The general goal of this method is to identify the parameters $\mathbf{a}_m$ of the model (1) that are most likely to have generated that set of k data points M_i, for each reference material during the training period.

3. VOLUMETRIC REPRESENTATION

3.1 Cutaneous and kinesthetic data integration

In this work, the structure of the in-hand explored object is represented using a volumetric framework analogous to an occupancy grid. Instead of the conventional binary occupancy status (occupied/empty), this work proposes an approach to represent the perceived softness characteristics of the explored regions of the object, by associating to each voxel of the volumetric representation a probabilistic distribution, $p(m_l|\mathbf{D}_k^l)$, that describes the similarity of the contact interaction signature of that region (after n samples M_i in that region represented by the voxel) with the contact interaction signature of the M reference materials, trained previously, that constitute the haptic memory of the system.

The proposed representation framework is suitable to be progressively updated as long as exploration progresses and new samples $\mathbf{M}_i$ are acquired. The distribution $p(m_l|\mathbf{D}_k^l)$ of a voxel l is updated if the location associated to the sample M_i is contained on that voxel. Each measurement $\mathbf{M}_i = (C_P, C_A, C_D)$ includes the cutaneous component $C_P(C_A)$ and the kinesthetic component $C_P(C_D)$. For each voxel l, the set $\mathbf{D}_n^l$ contains the n measurements $\mathbf{M}_i$ influencing the voxel l. The probability distribution function of the softness of voxel l given the $\mathbf{D}_n^l$ measurements influencing that voxel l is represented by $p(m_l|\mathbf{D}_n^l)$. As analogously demonstrated in [3] and [1], the following equation is used recursively to update the belief $p(m_l|\mathbf{D}_n^l)$ each time a new influencing sample $\mathbf{M}_i^l$ is obtained. The cutaneous tactile and kinesthetic information are integrated on this step.

$$p(m_l|\mathbf{D}_n^l) = \beta_1\beta_2 p(m_l|M_n^l)p(m_l|\mathbf{D}_{n-1}^l) \qquad (2)$$

The element $p(m_l|\mathbf{M}_i^l)$ of the previous equation represents a influence model of the measurements, whereby measurements $\mathbf{M}_i = (C_P, C_A, C_D)$ are converted in estimates of softness description m_l of a voxel l. The constants β_1 and β_2 are normalization constants ensuring that the left side of the equation sums up to one ever all m_l.

3.2 Local context information integration

The integration of the cutaneous and kinesthetic data is made using principles based on the occupancy grid framework. The independence assumption frequently causes voxels with a high uncertainty representation, not considering the representation of the neighbour voxels which can be used to improve (reduce the uncertainty) of the representation of that voxel. This processing stage consists in two processes: one related with the estimation of the representation of unexplored voxels based on the state of the neighbour explored voxels; the second one is related with the local continuity consistency verification between explored neighbour voxels. Vertical neighbourhoods are considered, because the exploration is performed by using vertical press and release movements.

3.2.1 Unexplored voxels extrapolation

In this first processing stage, for each volumetric column of the volumetric representation, if we consider ϑ_U as the set of

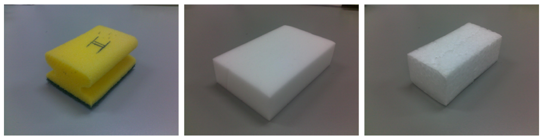

Figure 1: Set of the 3 reference materials, $Material_1$, $Material_2$ and $Material_3$, with different softness characteristics.

unexplored voxels with two (one upper and one lower)neighbour explored voxels, the estimation of the softness description of each of those unexplored voxels is based on the state of the lower and upper neighbour voxels and obtained by the expression:

$$\forall_l \in \vartheta_U,\ p(m_l|\mathbf{D}_n^l) = \frac{\sum_{i=1}^{2} \frac{1}{H(m_{li})} p(m_{li}|\mathbf{D}_n^l)}{\sum_{i=1}^{2} \frac{1}{H(m_{li})}} \qquad (3)$$

$H(m_{li})$ represents the entropy of the probabilistic representation associated with the voxel m_{li}. The index $l1$ and $l2$ refers to the vertically upper and lower neighbours of the voxel l, respectively. The more uncertain neighbours voxels have less contribution to the representation estimation of the unexplored voxel than the more certain ones. This extrapolation process also contributes to a faster reduction of the global uncertainty of the representation. The uncertainty of the representation is represented by the entropy.The entropy of each voxel, $H(m_l)$, can be formulated by the following expression:

$$H(m_l) = -\sum_{i=1}^{3} p(m_l = Material_i|D_n^l)\log(p(m_l = Material_i|D_n^l)) \qquad (4)$$

3.2.2 Local continuity consistency verification

The second processing stage is dedicated to the voxels already explored. In order to verify consistency of the local continuity of each volumetric column of the representation voxels ϑ_E, we considerer each voxel l and its lower neighbour $l1$:

$$\forall_l \in \vartheta_E,\ p(m_l|\mathbf{D}_n^l) = \frac{\sum_{i=0}^{1} \frac{1}{H(m_{li})} p(m_{li}|\mathbf{D}_n^l)}{\sum_{i=0}^{1} \frac{1}{H(m_{li})}} \qquad (5)$$

$H(m_{li})$ represents the entropy of the probabilistic representation associated with the voxel m_{li}.The index $l1$ and $l2$ refers to the vertically upper and lower neighbours of the voxel l, respectively.

4. EXPERIMENTAL PROTOCOL

During the experiments, the subject performing the exploration procedures wears a tactile distributed sensing array *Tekscan Grip* system and a motion tracker sensor *Polhemus Liberty*. The multi-modal data samples were individually timestamped by the software applications of each data acquisition devices using a millisecond (ms) resolution. The clocks of the different computers involved in the data acquisition architecture were synchronized using NTP (network time protocol).

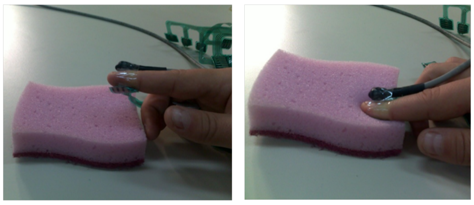

Figure 2: Active exploration of the novel object $Object_1$ using a motion tracker sensor *Polhemus Liberty* and a tactile distributed sensing array(4x4) *Tekscan Grip* system.

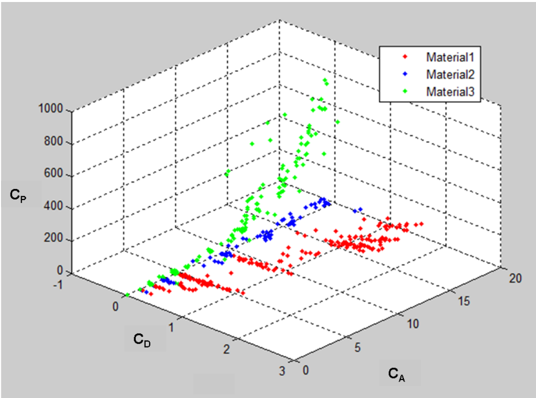

Figure 3: Representation of the distinct signatures $C_P(C_D, C_A)$ of the reference materials $Material_1$,$Material_2$ and $Material_3$.

• During the training period, samples of the 3 reference materials (Figure 1) are placed in the manipulation region of the experimental area. For each of the reference materials, the subject applies a unidirectional perpendicular pressure, using the index fingertip, against the surface of the sample. The subject has repeated this procedure 10 times for each reference material. For each reference material m, the set of data points of the format $\mathbf{M}_i = (C_P, C_A, C_D)$ are stored and used to estimate the parameters $\mathbf{a}_m = (a_1^m, a_2^m, a_3^m, a_4^m)$ which will characterize its dynamic signature.

• During the test period, the subjects are asked to actively explore a deformable object, $Object_1$, (Figure 2) novel to the system that has softness characteristics more similar with the reference material $Material_1$. The subject exploring the object uses a series of press and release movements, pressing the fingertip against the object surface. The press and release cycles are performed several times in the same region of the object surface, as well as, in different regions of the object in order to try to cover a representative extension of the object structure. The exploration movement can be supported with the other hand (passive hand) while the active hand explores the object. As long as the subject explores the objects, the data points $\mathbf{M}_i = (C_{P,i}; C_{A,i}; C_{D,i})$ are collected and used to progressively update the probabilistic volumetric representation of the softness of the object, $p(m_l|\mathbf{D}_n^l)$, for each voxel l.

5. RESULTS AND DISCUSSION

Table 1: Model parameters estimation for each reference material

Reference Material	a_1	a_2	a_3	a_4
$Material_1$	68.1	19.73	3.30	16.05
$Material_2$	365.6	16.01	2.77	7.64
$Material_3$	1832.00	$7.57{\times}10^{-6}$	9.309	$5.92{\times}10^{-6}$

5.1 Reference materials training sessions

For each reference material, by compiling the data of the press stages of the press and release finger movements and using the *Curve Fitting Toolbox* of MATLAB software, it is possible to test the estimation of the equations (1) corresponding to the model of those data representations $C_P(C_D)$ and $C_P(C_A)$. The results of the parameters estimation of the relations $C_P(C_D)$ and $C_P(C_A)$ are presented in Table 1 for each of the reference materials that constitute the haptic memory of the artificial perception system.

5.2 Volumetric representation update of novel objects

During the experimental session the novel object $Object_1$ was actively explored using a series of press and release movements (about 50 cycles along all the object extension), applied in discrete locations of the complete object surface. The explored voxels(spatial resolution of $\varepsilon = 0.25cm$)are represented using different colors, as described in Figure 4(a). The color of each voxel has an RGB color dependent of the values of $p(m_l|D_n^n)$. For each voxel l, $(Red, Green, Blue) = (p(m_l = Material_1|D_n^n), p(m_l = Material_2|D_n^n), p(m_l = Material_3|D_n^n))$. The numerical values are described in table 2. The novel object has perceived softness characteristics more similar with reference material $Material_1$. The representation uncertainty decreases as the exploration progresses from 50% to 100%. For higher levels of finger indentation (deeper voxels) in the natural shape of $Object_1$ the discriminability of the softness properties among the three reference materials increase.

In order to demonstrate the processing stage to verify the local vertical continuous consistency, the proposed approach was applied to the experimental data acquired during the 100% exploration of $Object_1$. The results are presented in table 2 and Figure 4(b). This processing stage contributes to improve the representation by analysing the vertical lower neighbour voxels of the explored voxels and update the representation of each voxel according with the influence of those voxels. Lower voxels (corresponding to higher indentations levels in the natural object shape surface) tend to have a better and correct discrimination between the three reference materials that compose the haptic memory of the system. Following this approach this better discrimination is propagated to the superficial voxels, contributing for the global improvement of the representation. The uncertainty of the representation decreases.

In order to analyse the impact of the proposed approach to estimate the softness description of unexplored regions by extrapolation of the vertical neighbour voxels the data extracted during the exploration of $Object_1$ was considered. Considering the data for the 100% exploration of the $Object_1$,

Table 2: $Object_1$ unaxial exploration data

$Object_1$												
	50%				100%				Continuous consistency verification			
	$p(m_l\|D_n^n)$			$H(l)$	$p(m_l\|D_n^n)$			$H(m_l)$	$p(m_l\|D_n^n)$			$H(l)$
l_1	0.4137	0.4077	0.1786	0.4510	0.4739	0.4573	0.0688	0.3891	0.5271	0.4431	0.0298	0.3487
l_2	0.5133	0.4862	0.0005	0.3027	0.5677	0.4323	0.0000	0.2970	0.7001	0.2999	0.0000	0.2652
l_3	0.6471	0.3529	0.0000	0.2918	0.7977	0.2023	0.0000	0.2187	0.9769	0.0231	0.0000	0.0478
l_4	0.9285	0.0715	0.0000	0.1118	0.9925	0.0075	0.0000	0.0191	0.9989	0.0011	0.0000	0.0036
l_5	0.9990	0.0010	0.0000	0.0033	0.9995	0.0005	0.0000	0.0018	0.9999	0.0001	0.0000	0.0004
l_6	0.7314	0.2686	0.0000	0.2527	0.9999	0.0001	0.0000	0.0002	0.9996	0.0001	0.0000	0.0017

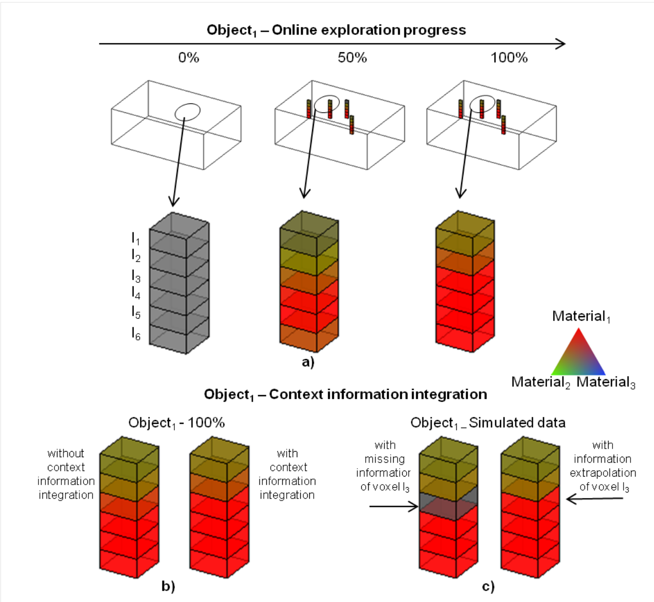

Figure 4: a)$Object_1$ volumetric representation during the progress of the exploration. b)Representation of a volumetric column before and after the continuous consistency verification stage. c)Representation of a volumetric column before and after the unexplored voxels extrapolation stage.

it was assumed that the voxel l_3 was not explored (Figure 4(c)). The corresponding representation is described by table 3. For voxel l_3 all the reference materials have an equal probability. If we apply the proposed approach, the representation of voxel l_3 is estimated by extrapolation of the representation of the vertically upper l_1 and lower l_3 neighbour voxels. The achieved estimated representation is described in table 3. As can be seen, by estimating a representation for that initially empty voxel, the total entropy(uncertainty) for that volumetric column sample representation has decreased.

Table 3: $Object_1$ extrapolation exploration data

voxel l_3				
	$p(m_l\|D_n^n)$			$H(m_l)$
Unexplored voxel	0.3333	0.3333	0.3333	0.4771
After extrapolation	0.9668	0.0332	0.0000	0.0633

6. CONCLUSIONS

This work has proposed a probabilistic volumetric representation framework to describe the softness characteristics of actively explored objects. The softness characteristics of each voxel are represented as a probabilistic combination of the behaviour of 3 reference materials (haptic memory of the system). The representation of the profiles $C_P(C_D, C_A)$ of each reference material has been used to demonstrated that the softness characteristics of the three different reference materials is distinct.

The proposed approach has been used to represent the softness characteristics at discrete spatial locations of a novel object to the system, ($Object_1$). Based on the simple integration of tactile cutaneous data and kinesthetic data it was possible to discriminate the softnesses properties of that new object. It was more similar with the reference material $Material_1$. The representation was improved as long as the exploration progressed. The application of the contextual information integration processing stages has contributed to decrease the uncertainty of the representation of the novel object $Object_1$.

7. ACKNOWLEDGMENTS

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