Can a soft robotic probe use stiffness control like a human finger to improve efficacy of haptic perception?

Nantachai Sornkarn, Student member, IEEE, and Thrishantha Nanayakkara, Senior member, IEEE

Abstract—When humans are asked to palpate a soft tissue to locate a hard nodule, they regulate the stiffness, speed, and force of the finger during examination. If we understand the relationship between these behavioral variables and haptic information gain (transfer entropy) during manual probing, we can improve the efficacy of soft robotic probes for soft tissue palpation, such as in tumor localization in minimally invasive surgery. Here, we recorded the muscle co-contraction activity of the finger using EMG sensors to address the question as to whether joint stiffness control during manual palpation plays an important role in the haptic information gain. To address this question, we used a soft robotic probe with a controllable stiffness joint and a force sensor mounted at the base to represent the function of the tendon in a biological finger. Then, we trained a Markov chain using muscle co-contraction patterns of human subjects, and used it to control the stiffness of the soft robotic probe in the same soft tissue palpation task. The soft robotic experiments showed that haptic information gain about the depth of the hard nodule can be maximized by varying the internal stiffness of the soft probe.

Index Terms—Morphological Computation, Active Haptic Perception, Proprioception, Robotic Palpation, Soft Robotic Probe.

1 INTRODUCTION

The nature of sensorimotor coupling and its implications on the very nature of computation of action-perception arbitration in soft robotics and biological motor control is not well understood yet. For instance, the spindle sensors (provide position and velocity feedback) and tendons (provide force/torque feedback) are physically embedded and connected among muscle fibres. That makes sensing entangled with action, offering opportunities to take control over haptic perception by changing muscle co-contraction. E.g. people palpate several times with varying finger stiffness when asked to discern physical properties of abnormality presented in a soft object.

In 1980s Vallbo and Johansson [1], [2] provided compelling evidence suggesting that the associative modulation of physical properties of the body in biological systems can enhance the proprioceptive feedback. This also suggests that the internal impedance state of the physical embodiment of the body, which mediates both sensing and actuation of an agent, can influence the quality of both action and perceived information [3]. In general, the sensing and motor functions in biological system are combined and often co-ordinated in order to improve the quality of action and maximize the sensory information gained [4]. Human’s grasping task serves as a very good example to explain the co-ordination between the sensing and motor functions. It was shown in previous study [5] that humans can induce learning and dexterity in object manipulation through the coordination of sensorimotor memories with haptic sensory feedback. This influences how the information flow is organised and structured within the sensorimotor network. It was further found that the organization of the information flow structure also depends on the placement and the controlled state of the body (“Morphological computation”) [3].

The regulation of internal impedance state and behavior of the body to enhance perception can be understood in general as “active sensing”. For example, in active haptic sensing, human would modulate the internal state of the body (muscle co-contraction) in order to regulate proprioceptive feedback [4], [6], [7]. This way, humans can build associations between haptic information with the behavioral variables to estimate the physical property of the environment [8]–[10]. For example, our recent study [11] shows that humans use different force/velocity control strategies during manual palpation to detect abnormality inside a soft silicon phantom. The regulation of these strategies are accompanied by behavioral variations like movement of fingers in different trajectories, velocities, frequencies, regulation of finger’s joint stiffness, and regulation of applied pressure and force at the finger tip [12].

The term morphological computation in this paper refers to the ability of an agent to control or vary its physical structure similar to how biological creatures behave in order to adapt to the task or environment [13]. In the case of action, it has been well established in previous studies that allowing the compliant body of a system to shape itself to the task-specific-environment can be viewed as an extra potential computational resource [14] and can lead to a simplification of the complex learning and controlling tasks [15]–[17].

In the context of perception, despite the advanced development of the passively functioning sensory devices, obtaining the reliable and precise sensory information in an uncertain environment still poses a great challenge in robotic community. Researchers have taken a number of

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different approaches on the active adaptation of sensor morphology to alter or enhance the physical stimuli retrieved from the dynamic environment to reliable desired information [7]. An agent can therefore, through an implementation of an appropriate morphological computation strategy, maximise the sensory information gained (transfer entropy) during the exploration of the environment. The studies of adaptation of sensor morphology include the change of physical structure of the sensor itself, such as: size [18], sensor’s placement [3], dimension [19], shape [20], and orientation [21]. Apart from the changes at the physical structure level of the sensor morphology, the control of the internal embodied structure coupled between the action and perception also play important role in active perception [22], [23]. Hence for the term ‘morphological computation’ in this paper, we focus on the regulation of internal stiffness at the embodiment level of the system.

As a case study for this paper, we used the task of estimating the depth of a hard nodule buried inside a soft object, i.e. soft silicon phantom, carried out by both human subjects and a robotic finger with variable stiffness control. It was shown in a previous study [24] that an artificial tactile sensor can outperform the humans capability in the passive detection of a lump embedded inside a soft phantom. In the study, haptic perception of human was limited to that from the passive tactile sensation perceived through mechanoreceptors at the finger distal phalanges. However, humans active touch behavior was not considered in the study. It was shown in [25] that by controlling the exploration speed, orientation, and voluntary movement, the performance of the perception can be enhanced during the active touch. The first experimental result presented in this paper also suggests that apart from the voluntary movement of the finger during manual palpation, the voluntary muscle co-contraction also shows variability. Therefore we suspect that the regulation of fingers internal impedance plays an important role in humans proprioceptive information during active exploration.

We investigate the role of internal impedance in proprioception using a soft robotic probe with a controllable stiffness Mckibben type joint to probe the soft silicon phantom. The soft robotic probe used in this study represents an abstracted version of the human finger with joints stiffness control mechanism. The soft robotic probe comprises of the force sensor at the base, so that the proprioceptive information is conditioned by the level of joints stiffness similar to how the biological fingers proprioceptive sensation functions. The stiffness of the soft robotic probe was controlled across trials according to the co-contraction strategy employed by human subjects. The humans co-contraction strategy was abstracted in the form of a Markov Decision Process from the electromyography (EMG) signals recorded from the human subjects.

From the experimental results, we found that: i) Human subjects varied the muscle co-contraction level (finger stiffness) during manual palpation to estimate the depth of a hard nodule in the soft phantom. ii) The controllable stiffness soft robotic probe improved its accuracy of estimating the depth of a hard nodule in the same soft phantom by implementing the humans muscle co-contraction strategy. The results are in line with our speculation in previous work [26], where a robotic manipulator can use transfer entropy to maximize sensory information gain of its own states by regulating the internal stiffness.

### TABLE 1
Description of acronyms and abbreviations

<table>
<thead>
<tr>
<th>Acronym/Abbreviations</th>
<th>Description</th>
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<tbody>
<tr>
<td>EMG</td>
<td>Electromyography</td>
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<tr>
<td>MCP</td>
<td>Metacarpophalangeal joint</td>
</tr>
<tr>
<td>FDS</td>
<td>Flexor digitorum superficialis</td>
</tr>
<tr>
<td>EDC</td>
<td>Extensor digitorum communis</td>
</tr>
<tr>
<td>DTS</td>
<td>Desktop direct transmission system</td>
</tr>
<tr>
<td>MVC</td>
<td>Maximum voluntary contraction</td>
</tr>
<tr>
<td>RMS</td>
<td>Root-Mean-Square</td>
</tr>
<tr>
<td>ABS</td>
<td>Acrylonitrile butadiene styrene plastic</td>
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<tr>
<td>ANOVA</td>
<td>Analysis of Variance</td>
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</table>

### TABLE 2
Description of mathematical notations

<table>
<thead>
<tr>
<th>Notations</th>
<th>Description</th>
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<tbody>
<tr>
<td>( s_{max}^i )</td>
<td>Maximum processed EMG signal measured at ( i^{th} ) muscle during MVC</td>
</tr>
<tr>
<td>( i )</td>
<td>Muscle index (( i = FD ) and ( ED )), where ( FD ) and ( ED ) refer to the FDS and EDC muscle</td>
</tr>
<tr>
<td>( s_i )</td>
<td>Processed EMG signal measured at ( i^{th} ) muscle during palpation experiment</td>
</tr>
<tr>
<td>( s_N )</td>
<td>Normalized EMG signal measured at ( i^{th} ) muscle during palpation experiment</td>
</tr>
<tr>
<td>( s_{max}^{CC} )</td>
<td>Maximum processed EMG signal measured during co-contraction of both FDS and EDC muscle in MVC</td>
</tr>
<tr>
<td>( s_{CC} )</td>
<td>EMG signal of co-contraction of both FDS and EDC muscle in palpation experiment</td>
</tr>
<tr>
<td>( s_{CC}^{i} )</td>
<td>Normalized EMG signal of the co-contraction</td>
</tr>
<tr>
<td>( d )</td>
<td>Depth of nodule</td>
</tr>
<tr>
<td>( S )</td>
<td>State of muscle co-contraction</td>
</tr>
<tr>
<td>( t )</td>
<td>Number of trial</td>
</tr>
<tr>
<td>( P_{S,t} )</td>
<td>Probability distribution of the co-contraction state at time ( t )</td>
</tr>
<tr>
<td>( M_{okk} )</td>
<td>Markov Decision Matrix</td>
</tr>
<tr>
<td>( \sigma_S )</td>
<td>Standard deviation of ( S ) state of muscle co-contraction</td>
</tr>
<tr>
<td>( S )</td>
<td>Expected value of ( S ) state of muscle co-contraction</td>
</tr>
<tr>
<td>( l0, l1, ) and ( l2 )</td>
<td>Length of probe’s links (connecting-, base-, and tip link, respectively)</td>
</tr>
<tr>
<td>( k_s )</td>
<td>Spring constant of the springs used in the probe</td>
</tr>
<tr>
<td>( K_s )</td>
<td>Probe’s joint stiffness rating</td>
</tr>
<tr>
<td>( q )</td>
<td>Rotational displacement of the probe’s joint</td>
</tr>
<tr>
<td>( R )</td>
<td>Radius of the probe’s pivot joint</td>
</tr>
<tr>
<td>( r_a )</td>
<td>Position of the anchor ring of the probe</td>
</tr>
<tr>
<td>( \tau_f )</td>
<td>Measured torque at the end of the probe’s base link</td>
</tr>
<tr>
<td>( P_{f}(d</td>
<td>\tau_f) )</td>
</tr>
<tr>
<td>( P_{f-1}(d) )</td>
<td>Prior probability distribution of nodule’s depth</td>
</tr>
<tr>
<td>( P(\tau_f</td>
<td>d, r_o) )</td>
</tr>
<tr>
<td>( \varphi )</td>
<td>Memory primitives</td>
</tr>
<tr>
<td>( G_{t} )</td>
<td>Information gained at ( t^{th})-iteration</td>
</tr>
<tr>
<td>( T )</td>
<td>Empirically specified threshold used in computing correlation distance between information gained</td>
</tr>
<tr>
<td>( d_e )</td>
<td>Actual nodule’s depth</td>
</tr>
<tr>
<td>( d_{est} )</td>
<td>Estimated nodule’s depth</td>
</tr>
<tr>
<td>( p )</td>
<td>Significance in ANOVA test</td>
</tr>
</tbody>
</table>

Section II focuses on the human manual palpation task to identify or estimate the depth of a hard nodule embedded inside a soft silicone phantom. Section III discusses results of nodule depth estimation using a controllable
stiffness soft robotic probe following humans muscle co-contracting strategy. Finally we provide concluding remarks and a discussion in section IV. The acronym, abbreviation, and mathematical notations used throughout the paper are described in Table I and II.

2 Manual Palpation Task to Identify the Depth of a Hard Nodule in a Soft Silicone Phantom

In this paper, we use a manual palpation task to derive deeper insights into the possible reasons as to why humans control finger stiffness during soft tissue palpation by testing their strategy in a controllable stiffness soft robotic probe to do the same task. Here we used 3 soft silicone phantoms as the samples in the experiments, where each contains a plastic bead with size of 15mm diameter embedded at 2, 4, and 8mm beneath the exposed surface of the phantom (see Figure 1). The silicone phantom is made from a soft clear silicone elastomer gel RTV27905 from Techsil.

![Fig. 1. (a) A soft silicone phantom fabricated using soft clear silicone elastomer gel with a spherical plastic bead of size 15mm diameter embedded inside at the depth of d = 2, 4, and 8mm. (b) Example of the finite element simulation of soft silicone phantom with an embedded hard nodule being palpated using an indenting fingertip [27].](image)

The ABS plastic bead, which hereafter refers as hard nodule, was embedded between two layers of silicone phantom - top and bottom layer. The given chemical substances (Part A and B) were mixed in 1:1 ratio according to fabricants specification. First, the top layer was created by pouring the mixture into the mold until the depth reaches the desired nodules depth, i.e. 2, 4, and 8mm. This layer is allowed to rest until completely cured. The nodule is then placed in the middle of the mold on this layer. Then the bottom layer was created by pouring the rest of the mixture into the same mold until the total height of the phantom reaches the height of 3cm. The whole phantom is allowed to cure until completely solid.

The hard nodule is stiffer than the soft silicone phantom used in this study. Therefore the contrast between the stiffness of the soft silicone phantom and the hard nodule represents a good approximation of the difference in the stiffness between the malignant tumor and healthy fibroglandular breast tissue [28]. The dynamic of the interaction behavior between the soft silicone phantom and hard nodule during palpation was simulated using finite element analysis in [27]. The simulation result is shown in Figure 1(b). This illustrates the distribution of stress and strain in FEM analysis during the contact between simulated phantom with hard nodule and the simulated finger tip. It is shown that the interaction is dynamic and not only the nodule is being felt; but also the combination of interaction behavior between the nodule and the tissue. This results in the dynamic response in humans finger.

2.1 Experimental Setup and Methodology

The main focus of this experiment is to understand how the muscle co-contraction level of the human forearm corresponding to the finger stiffness affects the estimation accuracy of depth of a hard nodule buried inside a soft silicone phantom. Here, we focus on the abduction and adduction activity of the finger, for which the metacarpophalangeal (MCP) joint is mainly responsible. It was shown in previous studies [30], [31] that the MCP joint of the index finger can be modulated by the co-contraction of the flexor and extensor muscle in the arm. Therefore this activity can be quantified through measurement of the muscle surface electromyography (EMG) of the major finger antagonistic muscle pair, namely: flexor digitorum superficialis (FDS) and extensor digitorum communis (EDC) muscles [32]. The location of this muscle pair is shown in the anatomical structure in Figure 2(a). The activity of the individual muscle is directly related to the muscle force. Since these two muscles are coupled with the MCP joint, the force from each muscle antagonistically affects the joint torque. Therefore, the internal impedance (stiffness) of the fingers joint increases with simultaneous increase of both FDS and EDC muscles activity.

The experiment involved 6 healthy subjects with no hand/wrist injury, in the age group of 20 - 43 years. This experimental protocol was approved by Kings College London Biomedical Sciences, Medicine, Dentistry, and Natural and Mathematical Sciences research ethics committee. During the experiment, subject was asked to sit in a relaxed posture with the dominant forearm resting on a lab desk. The subjects dominant hand was placed directly on top of the soft silicone phantom to palpate a soft tissue. A pair of wireless Desktop Direct Transmission System (DTS) for wireless EMG electrodes from NORAXON U.S.A, Inc. were attached to the subjects arm to capture the EMG signals at 1500Hz at FDS and EDC area as shown in Figure 2(b). To avoid noise and crosstalk from the EMG sensor, the skin was cleaned with alcohol before the electrodes were attached.

During the experiment, the EMG signal can be affected by many factors, both extrinsic and intrinsic. These include the placement of the electrodes, skins temperature and humidity [33], subjects individual muscle fiber composition [34], and anatomical structure of each individual. This can lead to the high variability of the EMG signal among subjects. Therefore the magnitude of muscle coactivation can differ between subjects due to aforementioned reasons. Hence prior to conducting the experiment, each subject was asked to perform a reference test. A reference test was conducted by asking each subject to hold and freely manipulate a mass weighing 5kg. The EMG signal from both FDS and EDC muscles were recorded during maximum voluntary contraction (MVC).

The experiments were divided into two phases for all subjects, namely: the training phase and the nodules depth...
of the nodule. At the end of each trial, subjects were asked in each estimation trial was 1 minute to estimate the depth
presentation in the estimation phase is shown in Table 4. The order of the phantom samples per each phantom sample) to avoid any bias learned during
human subjects were given the time of maximum 1 minute. Subjects were informed about the nodules depth in each
estimation phase. Firstly, in the training phase, subjects were asked to estimate the depth of the buried nodule. The question was “Please estimate the depth of a hard nodule based on your haptic perception”. The estimated depth was verbally
given to the experiment instructor at the end of each trial. The EMG signals during the estimation were recorded to explore the strategy used by human to estimate the depth of a nodule.

### Table 3
The order of presentation of phantom samples in the training phase

<table>
<thead>
<tr>
<th>Trial</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth [mm]</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>2</td>
<td>4</td>
</tr>
</tbody>
</table>

### Table 4
The order of presentation of phantom samples in the estimation phase

<table>
<thead>
<tr>
<th>Trial</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth [mm]</td>
<td>8</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td></td>
</tr>
</tbody>
</table>

estimation phase. Firstly, in the training phase, subjects were asked to palpate the soft silicone phantoms with hard
nodule embedded at different depths (shown in Figure 2(c)). Subjects were informed about the nodules depth in each palpation trial. The training phase was carried out for five trials per nodule’s depth level, where in each trial, the human subjects were given the time of maximum 1 minute. Subjects were allowed to rest between each trial. The order of the phantom samples presentation in the training phase is shown in Table 3. In the nodules depth estimation stage, subjects were asked to estimate the depth of a hard nodule during manual palpation. Here subjects were blindfolded to mitigate the aid of visual perception in the estimation of nodules depth. The identical set of phantoms with different nodule depths used in training phase were presented to the subject one at a time in a random order (with 5 repetitions per each phantom sample) to avoid any bias learned during the first training phase. The order of the phantom samples presentation in the estimation phase is shown in Table 4. The maximum amount of time given to each human subject in each estimation trial was 1 minute to estimate the depth of the nodule. At the end of each trial, subjects were asked
to estimate the depth of the buried nodule. The question was “Please estimate the depth of a hard nodule based on your haptic perception”. The estimated depth was verbally
given to the experiment instructor at the end of each trial. The EMG signals during the estimation were recorded to explore the strategy used by human to estimate the depth of a nodule.

### 2.2 Human’s manual palpation results

![Fig. 3. Sample of muscle activity quantified by the EMG signal during a human manual palpation trial to estimate the depth of a hard nodule embedded inside a soft silicone phantom. The EMG signals measured, $s_f$ ($i = FD$ and $ED$) from FDS and EDC muscle of the subjects dominant forearm are normalised against the respective EMG signals during MVC (a) and (b) show the normalised EMG signal, $s_f^{\text{norm}}$ from both FDS and EDC muscle pair respectively. The combination of the activities contributed from both muscles can be described as the co-contraction behavior of the muscle. The normalised co-contraction EMG signal, $s_{CC}^{\text{norm}}$ is shown in magenta curve in (c); whereas the red circles indicate the peaks extracted from this signal.](image)
The raw EMG signals from both EDC and FDS muscles captured during MVC and palpation activity of each subject were pre-processed by applying rectification and smoothing method with the use of Root-Mean-Square (RMS) processing, in order to remove the noise interference and signal artifacts that may be present in the raw EMG signal. During MVC activity, the maximum value of the processed EMG signals, $s_i^{max}$, from both FDS and EDC muscles, where $i = \text{FD}$ and $\text{ED}$ respectively, were recorded for each subject. $s_i^{max}$ were used as referencing value in the normalization of the EMG signal obtained during palpation trials. The pre-processed signals from both EDC and FDS muscle obtained during palpation are represented by $s_i$.

The pre-processed signals were normalized against the referencing values obtained prior the experiments during MVC activity, $s_i^{max}$.

$$s_i^N = \frac{s_i}{s_i^{max}},$$  \hspace{1cm} (1)

where $s_i^N$ represents the normalised EMG signal of each muscle. The example of the normalized EMG signals from FDS and EDC from one of the subjects during a palpation trial are shown in Figure 3(a) and (b). As mentioned previously in Section 2.1, the stiffness of the MCP finger joint increases with the simultaneous increase in muscle activity of antagonistically coupled FDS and EDC muscle pair (co-contraction). The total EMG can be computed by the summation of the rectified EMG signal from the FDS-EDC muscle pair [7]. This results in the co-contraction activity, which is similar to the way used to compute the stiffness synergy in the control of robot hand using EMG signal from FDS-EDC [7]. The EMG of co-contraction activity can therefore be represented by:

$$s_{CC} = \sum_i s_i,$$  \hspace{1cm} (2)

Hence, the normalised EMG of co-contraction activity can be computed as following:

$$s_{CC}^N = \frac{\sum_i s_i}{\sum_i s_i^{max}}.$$  \hspace{1cm} (3)

The total co-contraction results from the combined activation of both muscles is shown in Figure 3(c). The peak activation of the co-contraction during palpation can be directly extracted from the normalized co-contraction to observe the strategy employed for each trial given different sets of the environment. As highlighted in the sample signals shown in Figure 3(c), human modulates co-contraction activity of the muscles during estimation of the nodules depth.

The average estimation accuracy for each depth level at each trial across all subjects are shown in Figure 4(a). The average estimation accuracy of nodule’s depth at $d = 2 \text{ mm}$ increases from 65% to above 80% after first estimation trial; whereas the accuracy in estimation at other depth levels reaches maximum after second estimation trial. The average of estimation accuracy when nodule is buried at depth, $d = 4$ and $8 \text{ mm}$, reaches 65% at the 3rd estimation trial. The standard error for the nodule’s depth estimation tends to decrease slightly across trials. Further statistical analysis was performed to assess whether the number of trials and the depth of the nodule has the influence on the estimation.

The overall accuracy from the estimation of the nodule’s depth embedded inside a soft silicone phantom across all 6 subjects and all trials for each depth level is shown in Figure 4(b). It is shown that on average human can correctly estimate the depth of the nodule embedded at 2mm for 4 out of 5 trials (shown in blue bar); while the nodule buried at 4mm and deeper (shown in green and red bar respectively), the accuracy in nodule’s depth estimation drops to 56.7%. These result in the overall average estimation accuracy of around 65% (shown in magenta bar). We performed two-way ANOVA with post hoc Bonferroni correction to examine the effect of variation of nodule’s depth and number of trial on the nodule’s depth estimation. The two-way ANOVA showed no significant influence of the nodule’s depth level ($p > 0.05$), the number of trials ($p > 0.05$), and the interaction between the nodule’s depth level and number of trials ($p > 0.05$) on the accuracy of estimation. Since, both nodule’s depth level and the number of trials do not statistically influence the nodule’s depth estimation accuracy, we can further explore as to which factor may influence the estimation accuracy.

Here, we raise the question as to whether the humans use different muscle co-contraction strategies as shown in Figure 3 to obtain the accurate estimation of the environment (measured in transfer entropy of haptic perception) by recruiting finger’s internal stiffness dependent past haptic memories during soft tissue palpation. Therefore, it is interesting to explore the pattern of finger’s stiffness control, if
2.3 Extraction of Human’s Co-contraction Pattern Using Markov Chain Rule with Decision Matrix

In this section, we focus on the extraction and derivation of the generic pattern of finger’s stiffness control strategy derived from the subjects to the experiments given soft phantoms with nodule embedded at different depths. The strategy employed by human can be represented in a Markov chain which quantifies probability of moving from one level of muscle co-contraction to another (hereafter referred as “state”). The probability of the change in co-contraction level between the current state to the next state across all subjects during the nodule’s depth estimation for \(d = 2, 4, \) and \(8\) mm are normalized and presented in Figure 5(a), (b), and (c) respectively.

Therefore, if we assume that the initial co-contraction state \(S\) of the muscle pair is randomly sampled in each trial \(t\) from distribution \(P_{S,t}\) the probability distribution of next co-contraction state can be computed from the Markov Decision Matrix (state transition probability matrix), \(M_{mk}\) as given by:

\[
P_{S,t+1} = M_{mk}P_{S,t}
\]

It was found in [35] that the probability distribution of the surface EMG signal tends to be either super-Gaussian or Gaussian, depending on the contraction levels. Therefore for the simplicity, in this case, we treat the probability distribution of the state \(S\) to be Gaussian of the form:

\[
P_{S,t} = \frac{1}{\sigma_S \sqrt{2\pi}} e^{-\frac{(S - \mu_s)^2}{2\sigma_S^2}},
\]

with the expected value \(\mu_s\) and a standard deviation \(\sigma_S\). Since \(P_{S,t+1}\) does not have the same standard deviation of \(P_{S,t}\), we only take the expected value of \(P_{S,t+1}\) and reset the standard deviation to \(\sigma_S\) in trial \(t + 1\) in equation (4) to prevent the distribution from converging to a uniform distribution across trials.

The state transition probability shows that on average the regulation of co-contraction transition level tend to be on a diagonal line between the current and next transition. This suggest that the change in the level of co-contraction with respect to the current state occurs in small steps within the local muscle co-contraction region and large sudden changes are less likely to occur. Apart from the overall trends of the muscle co-contraction strategy human employed, it is important to also investigate the characteristics of the strategy used during manual palpation given different nodule’s depth levels by looking at the eigenvalues of each state transition probability matrix.

In a state transition probability matrix, the unit eigenvalue corresponds to the absorbing eigenvector. The rest of the eigenvalues correspond to the speed at which states converge to this absorbing vector. Since smaller eigenvalues make corresponding vector components to converge faster to the origin, the second largest eigenvalue dominates the overall behavior of the state transition probability matrix. The eigenvalues in Table 5 show a growth of the eigenvalues when the depth of the nodule increases. This indicates that regulation of stiffness (level of muscle co-contraction) undergoes a longer period of exploration before converging to an absorbing state when the depth increases.

3 Implementation of Human’s Co-contraction Strategy in the Controllable Stiffness Robotic Probe

The objective of this study is to derive deeper insights into the humans muscle co-contraction strategy during manual palpation to estimate the depth of the hard nodule. In this study, we used an abstracted version of the human finger to isolate and study the effect of joint stiffness control on the tendon force/torque sensor located at the base shown in Figure 6(a) as opposed to force measurement at the tip of the finger. The probe structure is mounted on a flippable ANT130 XY-stage (Aerotech Inc., resolution of 1nm) in the experimental setup as shown in Figure 6(b), which controls the position of palmar movement in \(x-\) and \(y-\) direction of the probe. The complete course of probe’s movement in each palpation trial is shown in Figure 6(c). The probe used in the experiments was designed based on the initial design presented in [26]. It is composed of three rigid links, namely: 1) connecting link of length \(l_0 = 143\) mm, 2) base link of length \(l_1 = 80\) mm, and 3) tip link of length \(l_2 = 70\) mm made from ABS plastics. The total length of this probe when the angle of pivot joint, \(\theta = 0\), is 293 mm. At the connection between the connecting link and base link, the torque around the \(x\)-axis is measured using an ATI Nano17 Force/Torque (F/T) transducer (SI-12-0.12, ATI Industrial Automation, USA, resolution of 0.015Nmm). The pivot joint coupled between the tip and base link comprises of a Mckibben type joint mechanism, which allows the regulation of joint’s stiffness. This mechanism consists of...
rating of the joint can be controlled. Therefore, in this paper, the joint stiffness rating of the probe is determined by the position of the anchor ring, $r_a$.

![Diagram of the probe's design](image)

**Fig. 6.** (a) Two-link probes design. It comprises of three links: connecting link, base link, and tip link, with the length of $l_2$, $l_1$, and $l_2$ respectively. A Firgelli L12 linear actuator is used to control the stiffness of the probe. The stiffness of the probe is controlled by changing the position of anchor ring, $r_a$. ATI Nano17 F/T transducer is mounted at the top-end of the base link to measure the torque during the interaction with soft silicone phantom. (b) Photo of the complete experimental platforms design comprising of the variable stiffness probe mounted on XY-stage during palpation to estimate the depth of an embedded nodule. The red translucent path graphically imposed in the photo indicates the probing path in the experiment. (c) shows the complete probing path (in red) in each trial from the top view over the silicone phantom. Black “X” indicates the origin position of the probe.

During the experiment with robotic probe, in each probing trial, the probe was programmed to probe along the sample in a sweeping motion in the mono direction of red solid arrow line (shown in Figure 6(c)) along the red path (shown in Figure 6(b)). The position of the probe was controlled by the XY-stage. At the end of each trial, XY-stage is programmed to move the probe back to its origin position (“X” in Figure 6(c)) through the red dotted path. The velocity of the probe during palpation was always kept constant at 20 mm/s. The torque, $\tau_f$, generated due to the interaction with soft tissue is measured at the rate of 1000 Hz around the F/T transducers x-axis, which is parallel to the axis of the probes pivot joint. The data acquisition only takes place when the probe is palpating over the soft silicone phantom (red solid line in Figure 6(c)). The measurement of $\tau_f$ and the control of $r_a$ were carried out via the program written in LabView2012 application, National Instrument, Corp., through data acquisition cards PCIe-6320 and NI-USB6341, respectively.

Since human subjects spend some time regulating the level of muscle co-contraction during manual palpation, we pose the hypothesis that stiffness regulation can exploit prior experience of proprioceptive sensors in known environments. Here, we test this using a laboratory made robotic probe that can regulate the internal stiffness to improve the accuracy of estimating an environmental variable (the depth of a buried nodule in a soft phantom in this case), by exploiting memory primitives contructed in multiple internal stiffness levels to maximize information gain in a Bayesian inferencing framework.

### 3.1 Construction of Probe’s Memory Primitives

Similar to the human experiment described earlier in this paper, the robotic probe experiment is also divided into
two parts. Firstly, the probe is allowed to explore the
environment under different probe’s stiffness for 25 trials. In
this instance, we present the probing experience during the
interaction with soft phantoms with nodules embedded
at different depth as ‘memory primitives’ in a form of
probability distribution of the measured quantity, \( \tau_f \), as a
function of probe’s internal stiffness, \( r_a \), and the environ-
mental parameter, i.e. the depth of nodule, \( d \), over multiple
learning trials. The recorded \( \tau_f \) from each trial was post-
processed in MATLAB R2013b application, MathWorks, Inc.
to create the memory primitives.

For this experiment, the memory primitives of peak
torque were constructed across 5 levels of stiffness rating,
\( r_a \), during the interaction with soft phantoms with nodule
embedded at 3 different depth levels, \( d \). This results in total
of 15 unique interaction conditions. Each measured torque
signal recorded from the F/T transducer is first de-noised.
The purpose of filtering the raw measured torque signal
obtained from the sensor was to remove the noise as well as
to discriminate the torque sensed during the interaction
at the location of hard nodule from that of normal soft
silicone phantom, which is subjected to the sudden changes
in the torque signal. Therefore, we used discrete wavelet
transform (DWT) with Daubechies mother wavelet, \( db10 \),
to decompose the raw torque signal for 5 decomposition
levels. This is because, in comparison with other technique
like fast Fourier Transform (FFT), DWT Daubechies is more
appropriate to detect sudden discontinuity in the signal
under the time domain [36]. From each de-noised torque
signal, the peak torque at the nodule’s location is extracted.

For each combination of given probe’s stiffness and
odules’ depth level, 25 palpation trials were repeated to
construct the memory primitives of the probe. The example
of shaded error bar with mean and standard deviation of
processed torque signal given different probe’s stiffness
levels across 25 trials during the interaction with phantom
with nodule embedded at 8 mm is shown in Figure 8. The
peak torque is extracted from the processed torque signal
around the location at which the probe went over the nodule
(shown as ‘o’ in the Figure 8). The probability distribution
of torque, \( P(\tau_f|d, r_a) \), can be generated by fitting a normal
distribution to the extracted peak torque data captured from
all 25 trials given a unique combination of different nodule’s
depth, \( d \), and probe’s stiffness, \( r_a \). The memory primitives
resulted from the training phase of the probe are shown in
Figure 9.

3.2 Bayesian Haptic Perception with Information Gain
Metrics with Stationary Probe’s Stiffness

From the non-linear relationship between the measured
torque at the base, \( \tau_f \), the internal stiffness of the probe’s
joint, \( r_a \), and the depth of buried nodule, \( d \), presented in
the memory primitives, an appropriate stochastic machine
learning technique can be implemented to understand the
role of varying the probe’s stiffness in solving the nodule’s
depth estimation problem during robotic palpation. It was
found in [37] that the machine learning algorithm that holds
the closest characteristics to that occurs in the central ner-
vous system in the brain for solving the interpretation and
the estimation problem is ‘Bayesian’ decision process. This
involves the systematical recruitment of prior beliefs and the
likelihood from the past experience. In this paper, for the
estimation of the nodule’s depth using the robotics probe,
we present Bayesian Inference approach to analyze the real-
time captured peak torque data during the palpation over
the nodule embedded inside silicone phantom given the
constant internal stiffness state of the probe. The memory
primitives constructed during the training phase are used
to estimate the depth of the nodule. The iterative equation
for Bayesian Inferencing is as follows:

\[
P_t(d|\tau_f) = \frac{P(\tau_f|d, r_a)P_{t-1}(d)}{\sum_{n=1}^{m} P(\tau_f|d, r_a)P_{t-1}(d_n)}, \quad (7)
\]

where \( t \) is the current estimation iteration, \( n \) is the index
of \( d \), and \( m = 3 \) is the number of possible nodule depths.
\( P_t(d|\tau_f) \) represents the posterior probability distribution
of nodule’s depth given the measured torque, \( \tau_f \), computed
from the prior distribution \( P_{t-1}(d) \) and the sampling or
likelihood probability distribution of torque, \( P(\tau_f|d, r_a) \),
given depths and different set of internal stiffness variable
presented in the memory primitives, \( \varphi \). The posterior
computed at each trial or iteration is then used to update the
probability distribution of the depth as a prior distribution
in the next iteration. The initial prior of the function \( P_{t=0}(d) \)
has a flat distribution across different depths, reflecting the
unbias probability.

If we consider a set of \( P_t(d|\tau_f) \) as the hypothesis of the
depth estimation, its entropy for a given torque measure-
ment \( \tau_f \), is dependent on probe’s internal stiffness \( r_a \), KL-
divergence defined in equation (8) represents the additional
information gained \( G_t \), about the relationship between the
hypothesis of depth estimation \( P_t(d) \), and \( \tau_f \) across itera-
tions of Bayesian Inferencing as well as across different sets
the probe’s stiffness. Therefore, KL-divergence is a good
measure to quantify the gain of different actions during the palpation.

\[ G_t = P_t(d|\tau_f) \log \frac{P_t(d|\tau_f)}{P_{t=0}(d)}, \]  
\( P_t(d|\tau_f) \) represents the probability distribution of depth estimation which is obtained from the Bayesian inference shown in Equation (7) at \( t \)th iteration, and \( P_{t=0}(d) \) represents the base hypothesis about the nodule’s depth estimation.

Kullback-Liebler transfer entropy is implemented in addition to the Bayesian Inference method to determine the number of measurement required to estimate the nodule’s depth by computing the correlation distance \( \delta \), between information gain of the current hypothesis, \( G_t \), and that of the prior hypothesis \( G_{t-1} \), in relation to the base prior distribution \( P_{t=0}(d) \). The palpation process stops at the point where the correlation distance is less than empirically specified threshold \( T = 0.0005 \), signifying that there is none to little change in the information gained across iterations.

In order to explore the influence of stiffness variation on the nodule’s depth estimation accuracy, two different algorithms were implemented. In the first algorithm, the probe’s stiffness was kept constant across iterations; whereas in the second algorithm the stiffness of the probe varies according to human’s co-contraction strategy. The depth estimation procedure for the case, where the probe’s stiffness is kept stationary across Bayesian iteration, is shown in Algorithm 1.

### 3.2.1 Results

Figure 10 exhibits the example of the progression of the nodule’s depth estimation (expected value and standard errors) across Bayesian inferencing iterations. As shown in these figures, the algorithm does not make any progress towards the convergence nor any change in the estimation as the Bayesian algorithm progresses. This may be resulting from the fact that the Bayesian inferencing algorithm is allowed to observe only in a single memory primitives by keeping the probe’s stiffness stationary.

By implementing the Bayesian inference algorithm, we can obtain an overall estimation accuracy of 66.7% with the
accuracy of 80, 60, 60% for nodule embedded at \( d_r = 2, 4, \) and 8 mm, respectively (shown in Figure 12, orange bars). The result on the estimation accuracy shows similar trend to that obtained in human experiment, where the depth of nodule embedded closer to the exposed surface of soft silicone phantom can be approximated more easily. It is important to note here that though the results show that on average the robotic probe provides slightly enhanced nodules depth estimation accuracy in comparison to those conducted by human (shown in Figure 12, green bars); it cannot be misinterpreted that the fixed stiffness strategy (performed by robotic probe) can outperform the humans finger stiffness control strategy. The differences in the absolute values of accuracy obviously come from the robots ability to retrieve multiple memories with perfect accuracy and to be able to sense using an advanced sensor. In the next section, we explore how humans strategy in estimating nodules depth obtained in previous experiment can be implemented to increase the estimation accuracy.

### 3.3 Bayesian Haptic Perception with Information Gain Metrics computed based on Human’s Stiffness Control Strategy

In this section, we explore whether the variation of probe’s joint stiffness like human can improve the efficacy in the estimation of the nodule’s depth. We implement the extracted human’s co-contraction strategy in palpation in the form of a Markov chain in the Bayesian haptic perception with variable probe’s stiffness across iterations for nodule’s depth estimation algorithm. Unlike the algorithm used in previous section where the estimation procedure is constrained by the exploration under a single memory primitive (fixed probe’s stiffness) across iterations in each estimation procedure; this active Bayesian algorithm allows change in the probe’s stiffness across iterations. The probe’s stiffness across each iteration is modulated based on the Markov decision matrices obtained in Section 2.3 and current level of probe’s stiffness. In order to utilize the Markov decision matrices, we can correspond levels of probe’s stiffness available in memory primitives to the co-contraction levels from the Markov decision matrices as shown in Table 6.

**Table 6**

<table>
<thead>
<tr>
<th>Probe’s internal stiffness, ( r_a ) [mm]</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human’s avg. co-contraction levels</td>
<td>0.1</td>
<td>0.2</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
</tr>
</tbody>
</table>

We explore whether the accuracy of nodule’s depth estimation can be enhanced by the modulation of probe’s stiffness based on human’s co-contraction strategy in palpation. In order to assess this, we perform a similar estimation procedure as shown in Algorithm 2. At the end of each iteration, the probe’s stiffness is changed using Markov chain rule. This process is repeated for 100 trials for each phantom.

#### 3.3.1 Results

Figure 11 depicts the average nodule’s depth estimation across 100 estimation trials at each Bayesian inferencing iteration. Since, most of the estimation trials tend to converge within 5 Bayesian iterations or less, here we only present the converging progression of the nodule’s depth estimation up to 6th Bayesian iterations. As shown in these figures, as the Bayesian inferencing algorithm progresses, the nodule’s depth estimation converges towards the actual nodule’s depth, although this happens at different rate. The rate of the convergence is directly proportional with the depth of the nodule. As the nodule is buried deeper from the exposed surface, the higher the number of iteration is required for the algorithm to converge. On the contrary to the previous algorithm, where the probe’s stiffness is kept stationary across iteration (shown in Figure 10), here the algorithm is allowed to explore in multiple memory primitives by regulating the joint’s stiffness based on human’s stiffness control strategy. Therefore, this allows the depth’s estimation to converge towards the actual nodule’s depth, \( d_r \).

The overall average accuracy from 100 trials of nodule’s depth estimation using Bayesian Inference with KL-Transfer Entropy together with the stiffness modulation based on average human’s co-contraction strategy across iterations reaches slightly above 90% as shown in Figure 12 in blue bar. The estimation accuracy from all individual actual depths are also higher in comparison to those with stationary \( r_a \).

![Algorithm 2: Nodule’s depth estimation algorithm using Bayesian Inference and KL divergence with Human’s co-contraction strategy](image-url)
Fig. 11. The average of mean and standard errors of the estimated nodule’s depth at each Bayesian iteration across 100 iterations with human’s stiffness control strategy. The actual depths of the nodule assessed here include \( d_r = 2 \), 4, and 8 mm, shown in (a), (b), and (c) respectively.

Fig. 12. Overall average nodule’s depth estimation accuracy and standard error resulted from 1) average human’s estimation across 6 subjects (shown in green), 2) the Bayesian Inference together with the KL-Transfer Entropy with fixed probes stiffness across iterations (shown in orange), and 3) the Bayesian Inference together with the KL-Transfer Entropy with extracted human’s co-contraction strategy (shown in blue).

### 3.4 Statistical Analysis of the Results

In addition, the ANOVA test was performed on the estimation result to assess the influence of the nodule’s depth level and the probe’s stiffness level, in the case where the probe’s stiffness is kept stationary across iterations. The ANOVA revealed significant differences between different nodule’s depth levels \( p < 0.05 \) as well as between the probe’s stiffness level \( p < 0.05 \). The interaction between the depth level and the probe’s stiffness level was also significant \( p < 0.05 \). Post hoc comparisons using the Bonferroni correction revealed that for the estimation accuracy of the nodule embedded at 2 mm beneath the surface is statistically significantly higher than the other depth levels. For the cases, where nodule is embedded at 4 mm and below, the difference in the estimation accuracy was not significant. Post hoc comparison further suggested that the probe’s stiffness level can be statistically separated into three groups based on the significant difference. The results suggested that the stiff probe \( (r_a = 16 \text{ mm}) \) can statistically obtain higher accuracy when the probe’s stiffness is fixed.

Lastly, multiple factor ANOVA with Bonferroni correction test was performed on the nodule’s depth estimation accuracy given different nodule’s depth and different experiments (1. human, 2. robotic probe with static stiffness, and 3. robotic probe with variable stiffness generated from Markov stiffness probability transition matrices shown in Figure 5). Multiple factor ANOVA test revealed that the nodule’s depth level had statistically significant influence on the estimation accuracy \( p < 0.05 \), and the type of experiments also statistically significantly influenced the depth estimation results \( p < 0.05 \). However, the interaction between these factors did not have statistically significant influence on the nodule’s depth estimation \( p > 0.05 \). Post hoc analysis also suggested that the result from the human experiment and the robotic probe with static stiffness do not differ statistically. On the other hand, the robotics probe can statistically significantly enhance the nodule’s depth estimation accuracy when using variable stiffness strategy generated from Markov matrices as opposed to the static stiffness strategy \( p < 0.05 \).

### 4 Discussion and Conclusion

In this paper, we have explored the role of internal impedance of both a controllable stiffness robotic probe and human counterparts in the accuracy in estimating a physical property of the environment - in this case, the depth of a hard nodule in a soft tissue. Here, we raised the question as to whether human modulates the internal stiffness of the finger in order to interpret the information perceived from sensory receptors and to enhance the accuracy in estimation of the physical properties of the environment, i.e. nodule’s depth, during manual palpation. The experiments discussed in this paper are separated into two main parts, namely: human experiment, and robotic probe experiment.

Human’s muscle co-contraction behavior during palpation may arise from multiple sources apart from the regulation of MCP joint stiffness, since human’s finger is composed of multiple joints. However, in order to isolate and study the effect of joint stiffness control on the tendon force/torque sensor located at the base as opposed to force measurement at the tip of the finger, the design of the robotic probe with single variable joint stiffness used in the experiment represents an abstracted version of human’s finger. Therefore, an exact replica of a finger with multiple parameters cannot conclude anything clear about this particular effect. In addition, during human’s manual palpation, the movement of the finger was not constrained within a single plane. However, if the experiment with robotic probe was carried out in similar manner (with movement trajectory), the effect of the variation of joint’s stiffness in the estimation of nodule’s depth cannot be properly assessed. Therefore, the probing direction of the robotic probe was kept to one plane to focus on the effect of the joint stiffness alone in information gain. Once these individual effects are well understood, they provide a firm foundation to design more complex robotic probing behaviors, which is beyond the scope of this paper.

The robotic probe with the implementation of human’s co-contraction strategy was compared with the case, where...
the robotic probe attains the stationary stiffness level across Bayesian iterations. Our results show that the efficacy of haptic perception does not depend only on the configuration of the finger as reported in previous studies [24] on passive perception, but also on the way internal impedance of the finger is regulated. Our results from the experiment with human subjects suggest that humans perform active exploration during manual palpation. Using the robotic probe, we showed that active probing allows the integration of knowledge available so far with new evidence accompanied by active regulation of bodily parameters like the joint stiffness.

Additionally, we showed that the robotic probe can improve accuracy in estimation from approximately 70 to 90% through active exploration in a Bayesian inferencing framework. Active Bayesian haptic perception in a robotic probe involves stiffness variation following a Markov decision process identified using human muscle co-contraction data. The increase in accuracy is mainly due to the ability of the estimation process to search in multiple memory primitive spaces as opposed to a single one in case of the passive mode. Therefore, we can conclude that the internal impedance control plays an important role in robotic haptic perception and in that of the biological counterparts.

It is noteworthy that in biological counterparts, haptic perception is the result of the integration of both tactile and proprioceptive stimuli [38], [39]. The processing of both stimuli are always combined during haptic sensation, regardless of whether those information are relevant in a particular task [40]. It has been found in a previous study on the human’s haptic perception [41] that the small number of different sensory stimuli (single channel of tactile and single channel of proprioception) is preferred over a large number of the same type of sensory stimuli (multiple channels of tactile) alone.

The nature of sensorimotor network in biological system has been greatly influencing our design and approach towards the biologically-inspired artificial systems. For example, it has been shown that, the understanding of the co-ordination of motor and sensory correlation patterns in human (often referred to as “synergy”) could well lead to an advancement and optimization of design of artificial system like wearable device, such as glove-based ‘Hand Pose Reconstruction’ system [42]. Furthermore, it was shown in [32] that humans can exploit stiffness synergy from their muscle pair controlling the impedance of the fingers joints to control stable robotics hands grasping.

Our results in this paper provide additional evidence to this phenomenon in terms of how humans might be regulating proprioception through stiffness control of the muscles that carry the proprioceptive sensors. It was shown in [5] that humans employ sensorimotor memory in order to coordinate sensory feedback and motor control in dexterous manipulation of object. We showed in this paper using robotic approach that the integration of sensory feedback with past proprioceptive memory through the variation of internal impedance can also enhance the accuracy of estimation of the environment.

In the future, if the nodule at the deeper depth is to be detected, the robotic probe with a larger stiffness range should be designed. However, detecting the nodule at deeper depth is beyond the scope of this paper. In addition, our previous work shows [11] that humans regulate force and velocity during manual palpation. Therefore, it would be interesting to add such behavioral variation on top of the stiffness control to study the interaction between the stiffness and behavior. While the functionalities of both tactile and proprioceptive sensations have been extensively studied in biology [43]–[45]; the integrative view on how the stimuli perceived from these sensations are organized, regulated, exchanged, and processed are still not fully understood. Therefore, it would be interesting to further explore the sensory coordination and how the information exchange or inference can enhance the perception and interpretation of the environment during active exploration of an artificial system, i.e. robotic device.

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**REFERENCES**


