Inexpensive Tactile Robotics

Benchmarking state-of-the-art tactile sensing using deep learning, using an inexpensive robot platform

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CHAPTER 1

INTRODUCTION

1.1 The importance of tactile sensing

Haptic sensing has long been acknowledged as critical for physical human interaction, with 'touch' holding a place as one of Aristotle's original conception of 'the five senses' [1]. To date, a substantial body of behavioural and neuroscience research demonstrates that haptic feedback is especially important (among human perceptions) for manipulation of objects. [2].

In the human body, the haptic sensory system processes information aggregated from two different sources [2]:

- **Cutaneous inputs** from *mechanoreceptors* and *thermoreceptors* embedded in the skin (also known as *tactile perception*).
- **Kinesthetic inputs** from *mechanoroceptors* in the muscles (also known as *proprioception*).

Both cutaneous and kinesthetic inputs contribute to the internal model that we use as humans to rationalise and interact with the world. This thesis will follow existing tactile literature terminology [3] by using the terms:

- **Sensing** to refer to the process of transduction, and signal processing by which contact with a tactile stimulus is converted into a (digital) signal
- **Perception** to refer to the process of synthesising sensor data into an observation.

Perception extends to combining data from different modalities in order to improve the robotic system understanding of its physical environment. For instance vision and tactile modalities are commonly fused in manipulation tasks (fig. 1.1).

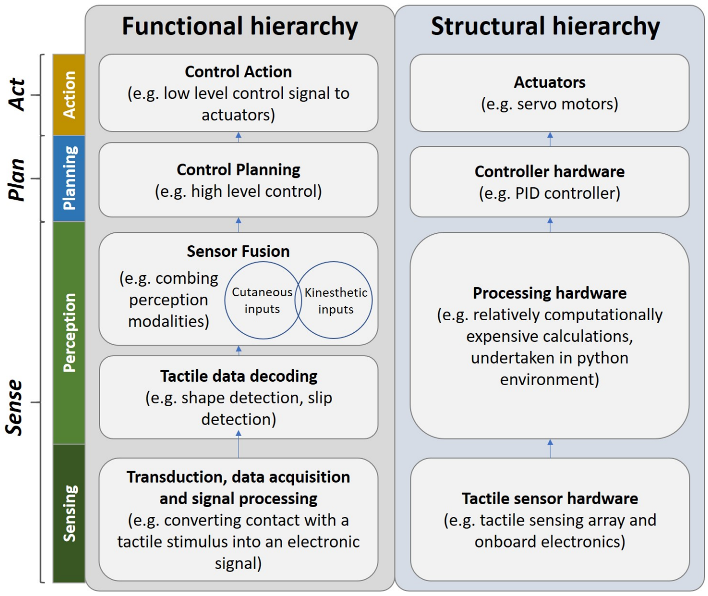

FIGURE 1.1. Hierarchical block diagram for a tactile sensing system, and linkage to the 'Sense-Plan-Act' robotic architecture framework. Adapted from papers [4] [3] [5]

Cutaneous inputs are particularly important for tactile perception because they convey information about the shape and location of objects. These are the only sensory inputs in the body that directly measure contact forces, and thus our interactions with our physical environment. They hold high intrinsic importance, this could be one of the reasons why these inputs have a "clear precedence over vision and hearing in prenatal development" of the human body [6]. Many experiments [7] [8] demonstrate that the kinesthetic sensory modality alone cannot compensate for the lack of cutaneous information if this is removed. This can easily be visualised by imagining trying to unzip a coat, or manipulate an object precisely whilst wearing thick gloves.

Yet across the domains of robotics and perceptual development, haptic perception is considered to lag behind vision and audition in both the volume of applied research and technological developments [9] [6]. Robotic dexterous manipulation does not currently match human capability. A current empirical example of this is highlighted by authors of recent 'Open AI' research showcasing dexterous in hand manipulation, implemented by reinforcement learning on a shadow robot hand platform. The authors specifically choose to omit data from the inbuilt biotac tactile sensors in system due to their introduction of high amounts of noise into the perception system. [10] [11] Although it is arguable that biotac is no longer a 'state of the art' sensor in the academic domain, it is still commonly used in research because it is one of few commercially available sensors. This example highlights the need for tactile sensing improvement in commercially available systems.

This need is relevant because many of the medium term aspirations set out by universities, global governments and industrial organisations (i.e. key societal institutions) require complex physical interactions with objects for increased automation [12] [13]. For example the 2019 Massachusetts Institute of Technology (MIT) report "The work of the future" [14] envisages a significant future roll for 'collaborative robots' which augment human counterparts capabilities in high quality human jobs. The report sees future robots as substitutes for mundane human tasks. Including tasks outside of factories such as "such as stocking, transporting, and cleaning, as well as awkward physical tasks that require picking, harvesting, stooping, or crouching (as in arenas like agriculture)". An observation that can be made is that all of these tasks envisaged for the 'work of the future' require complex object interaction. Indeed a general observation is that the range of manipulation tasks for which humans employ tactile sensing is substantial.

1.2 Application of deep learning methods to tactile sensing

Although historically the development of tactile sensors extended to fabrication from entirely stiff materials, modern implementations of fingertip like sensors mostly incorporate soft, compliant materials which mimic the flexible nature of human skin [4] . These 'soft robotic' properties are desirable in tactile sensing because the morphology of soft materials allows them to conform to the shape of a stimuli, and enables effective transduction of the contact. For example when estimating contact forces, or the relative pose of a stimuli in contact with the fingertip.

However these soft robotic materials pose challenges for tactile perception. Primarily this is because capturing data to describe the myriad shapes that can be adopted by a flexible tactile sensor is necessarily high-dimensional. Conversely the desired perception output is nearly always low dimensional (e.g. contact force distribution, shear force distribution, and stimuli pose relative to sensor). Finding the relationships between this high-dimensional data, and the desired low dimensional outputs is a challenge because the mapping will almost always be complex and highly non linear [15].

Initially these challenges were addressed in research using interaction matricies and jacobian methods to relate sensor data to tactile perception outputs. This allowed tactile sensors to be incorporated into manipulation control schemes [16]. However this approach is limited only to constrained tasks because of limitations in the tactile mapping performance. For example this approach was limited to low degree of freedom grasping.

Deep learning (using artificial neural networks) has proven especially well suited for mapping high dimensional tactile data to low dimensional outputs in tactile control schemes. This is because deep neural network structures are effective in the extraction of particular features from sensor data, removing the need for human engineered features. This is the case even for highly non linear relationships between the data and the desired outputs.

Leveraging deep learning has resulted in notable advances in control using tactile perception. This includes improvements in robustness of grasping methods [17] [18], tactile servo control [15], and in hand manipulation of objects [19].

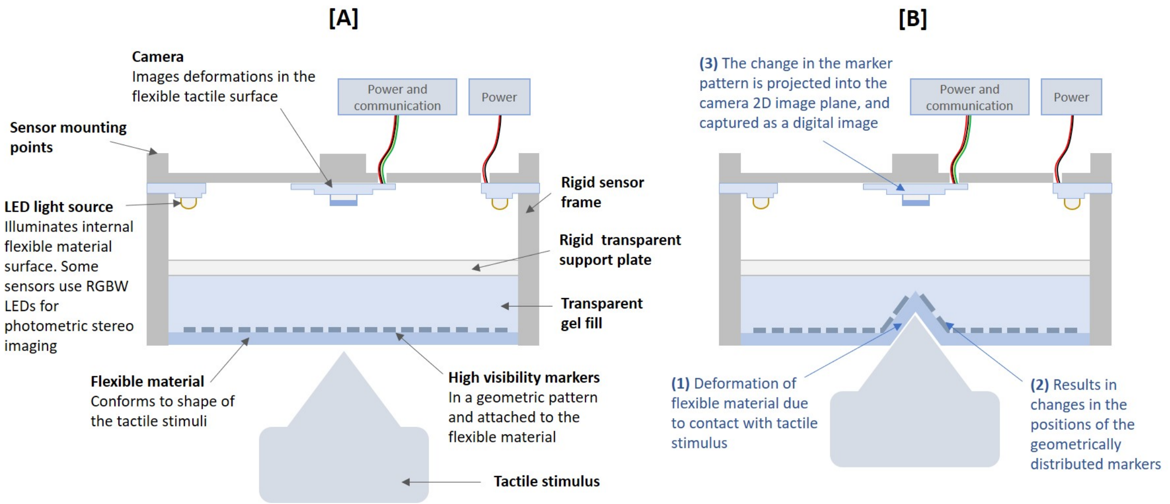

FIGURE 1.2. Cross section of a typical optical tactile sensor. Illustrates architecture, and transduction working principal. **[A]** Sensor is not in contact with tactile stimulus. **[B]** Sensor is in contact with tactile stimulus. Figure adapted from [23] [24]

State of the art tactile research is increasingly adopting a deep learning approach. At ICRA 2020 for the workshop “ViTac 2020: Closing the Perception-Action Loop with Vision and Tactile Sensing” three out of six accepted papers used Deep Neural Networks directly on pre-processed tactile sensor data [20] [21] [22].

Another closely intertwined trend is a widespread (but not universal) adoption of optical based tactile sensors for state-of-the-art research. Examples of this sensor are the Tactip [23], the Gelsight [24] and the Digit [19]. This type of tactile sensor uses a camera to image a flexible sensor surface in contact with a tactile stimuli (Figure 1.2). The use of camera technology in this type of sensor is linked to a high potential to leverage rapidly advancing computer vision research, as well as relatively cheap hardware (principally driven by the mobile phone industry).

1.3 Barriers to tactile sensing research

Integrating touch sensing into robotic manipulation platforms has proved challenging, and there is acknowledgement in the tactile research community that there remain significant barriers to entry for researchers hoping to apply novel deep learning methods to this field [19] [15]. These include:

- **The high cost of tactile sensors:** The cost of commercially available tactile sensors is high. For example a biotac system costs approximately $10,000 [25]
- **The high cost of robot platforms:** The robotic platforms required for experiments are

generally high cost. For example robot arms used in tactile research are normally above $10,000. More detail is given in Chapter 2

- **Insufficient hardware knowledge transfer:** There are few state-of-the-art open-sourced tactile sensors [19]
- **The need for resource intensive data collection:** Deep learning requires the collection of large tactile datasets, there are not widely adopted standard databases in this space.
- **The interest level in and demand for tactile research:** The amount of research funded in a field also depends on factors that are difficult to quantify, for example 'public interest' and 'commercial interest'

There is emerging research effort to redress some of these problems. For example sensor hardware cost is a theme that has been addressed through iterative design of various tactile sensors [23]. At ICRA 2020 researchers from facebook research released an open-source state-of-the-art tactile sensor named "Digit" with a working principle similar to the gelsight [19]. They estimate the manufacturing cost to be $15.

Widely used datasets that incorporate tactile data are still uncommon although there are some examples of this [26] [27] [28]. Future datasets could allow some experimentation to be completed in simulation, forgoing hardware cost. However adoption of standard databases (comparable to MNIST, CIFAR-10 in computer vision) has not been realised to date. [29] [30]

For novel experiments outside of simulation, the cost of the host robot platform for a tactile sensor still remains a significant barrier to entry. Typically during experiments involving robot control: tactile sensors are mounted on robot grippers [31], anthropomorphic hands [32], or as end effectors attached to a robot arm [15].

1.4 Research Questions

1.4.1 Primary Research Question: *Can inexpensive, lower capability robotic platforms lower the barrier of entry for tactile research?*

1.4.1.1 Motivation

A valuable research contribution is to investigate the relative performance of 'state-of-the-art' tactile research tasks on a robot platform that has lower cost but also lower capability (especially lower degree of freedom movement, lower repeatability) relative to current robotic tactile research platforms.

Quantitatively benchmarking the merits and limitations of using (relative) low cost platforms for state-of-the-art tactile sensing tasks has the potential to reduce barriers for further state-of-the-art tactile research. Many robotic low cost platforms use similar stepper, or 'smart servo' motors to control the motion of their actuated joints. Typically these joints are directly driven, without a gear mechanism. This results in aspects of their specifications (payload, repeatability) beings linked to these motors. And so benchmarking tactile sensing tasks, as well as demonstrating novel tactile experimentation on even one such example of a low-cost platform could unlock general confidence in similar platforms.

Extending this rationale by carrying out novel state-of-the-art tactile sensing research on this platform will add further weight to any conclusions that are drawn.

1.4.1.2 Hypothesis

The hypothesis for this primary research question is that 'Inexpensive, lower capability tactile robot platforms can achieve the necessary functionality to:

1. implement state of the art tactile sensing tasks, and
2. extend research in application of state-of-the-art methods to tactile sensing

In the context of this research and hypothesis *'inexpensive'* refers to educational robot platforms and sensors that are significantly less cost than current robot platforms which have been utilized by published papers state-of-the-art research. These platforms are generally more readily available and have fewer safety barriers to use. *'Lower capability'* refers generally to a range of robot platform characteristics including, but not limited to: Accuracy and repeatability, response time, payload, workspace and degrees of freedom.

1.4.2 Secondary Research Question: *Can a state of the art tactile servoing demo be implemented on an inexpensive, portable robotic platform?*

The interest level in, and demand for tactile research fundamentally depends on the ability of researchers to effectively communicate the functionality of the research outcomes that are realised. This is achieved in a lot of ways, and through various mediums (e.g. academic literature, conferences, internet hosted video).

The ability to demonstrate 'live' closed loop tactile servoing is certainly not novel. But generally demonstrations are undertaken on physically large robots

As part and parcel of this thesis, a goal is to implement a highly portable tactile robotics demonstration, specifically for the *Turing AI presents conference*. This conference has been delayed by Covid-19 but is due to be reconvened in early 2021.

It is noted here that the primary and secondary research questions are linked to two distinct goals for this masters thesis. The goals for each are clear, and the outcomes for each will clearly be reported separately within this document.

1.5 Aims and objectives

1.5.1 Aims

The high level aims of this research are to:

- **Benchmark tactile accuracy** of a sensor deployed on an 'inexpensive, lower capability robot platform' against robot platforms currently used for state-of-the-art research.
- **Compare performance for low level control** of an 'inexpensive, lower capability robot platform' when used for state-of-the-art tactile research tasks. This includes tactile servoing in a 2D plane, and over a 3D surface.
- **[HOLD] Compare performance for high level control** of an 'inexpensive, lower capability robot platform' when used for state-of-the-art tactile research tasks. This includes high level tactile reinforcement learning tasks both learnt on the robot and in simulation.

1.5.2 Objectives

- **Assess and identify:** suitable robot arm platform for integration as a low-cost tactile robot system.
- **Software integration:** to implement functionality comparable to current (higher cost) experimental robot systems.
- **Functional testing:** to verify that the functionality of the robot arm platform meets the functional requirements for state-of-the-art tactile experimentation
- **Experimentation:** Quantify differences in performance for lower cost, lower capability systems vs higher cost systems for current state of the art tactile experiment tasks with low level control.
- **Extension:** Demonstrate that the inexpensive system can implement novel state of the art experimental functionality with high level control. Benchmark this performance against robot arm systems currently used for state-of-the-art research.

1.6 Report Structure

The purpose of **Chapter 1** has been to provide context for tactile robotics, and to outline the main reasons why this study is a valuable academic contribution to the tactile sensing field.

Chapter 2 explores existing research in the field of tactile sensing. Recent advancements in the field of tactile robotics are highlighted especially those related to Deep Learning and tactile servoing. A variety of robotic platforms that have been used for recent state-of-the art tactile research are compared.

Chapter 3 describes the implementation of software and hardware integration for the Dobot Magician robot platform, which permits functionality comparable to current (higher cost) experimental robot arm systems.

Chapter 4 reports on experimental results output from testing of a tactile deep neural network model in an 'offline' setting. These results allow conclusions to be drawn about the fundamental accuracy of the Dobot Magician when undertaking servoing tasks with Tactip sensor mounted to its end effector.

Chapter 5 reports on a series of experimental results output from state-of-the-art tacitle servoing tasks undertaken on the Dobot Magician robot arm using a Tactip tactile sensor.

Chapter 6 reports on ... [HOLD, TBD]

Finally, **Chapter 7** provides a conclusion, summarising the key experimental findings of the research project and detailing possible future research direction.

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