Inexpensive Tactile Robotics

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

By

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Abstract

Here goes the abstract

Dedication and acknowledgements

Here goes the dedication.

Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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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).

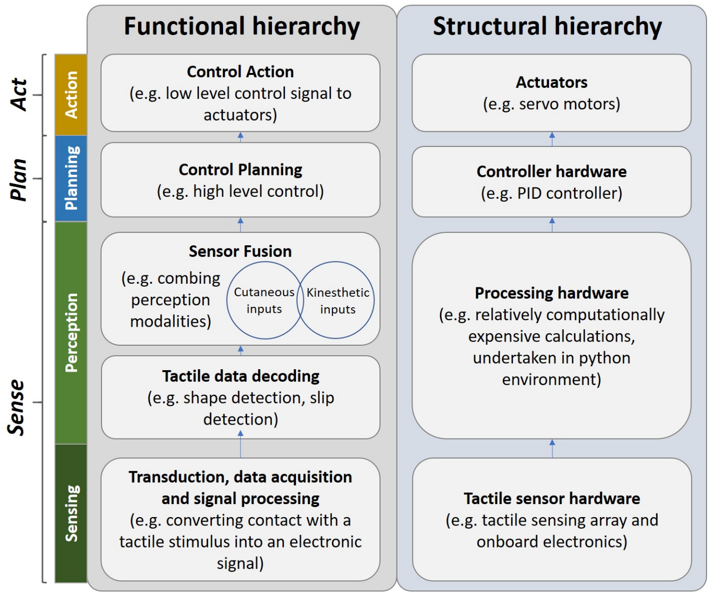

FIGURE 1.1. Hierarchical block diagram for a tactile sensing system, and linkage to the 'Sense-Plan-Act' robotic architecture framework. Adapted from papers [4] [3] [5]

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].

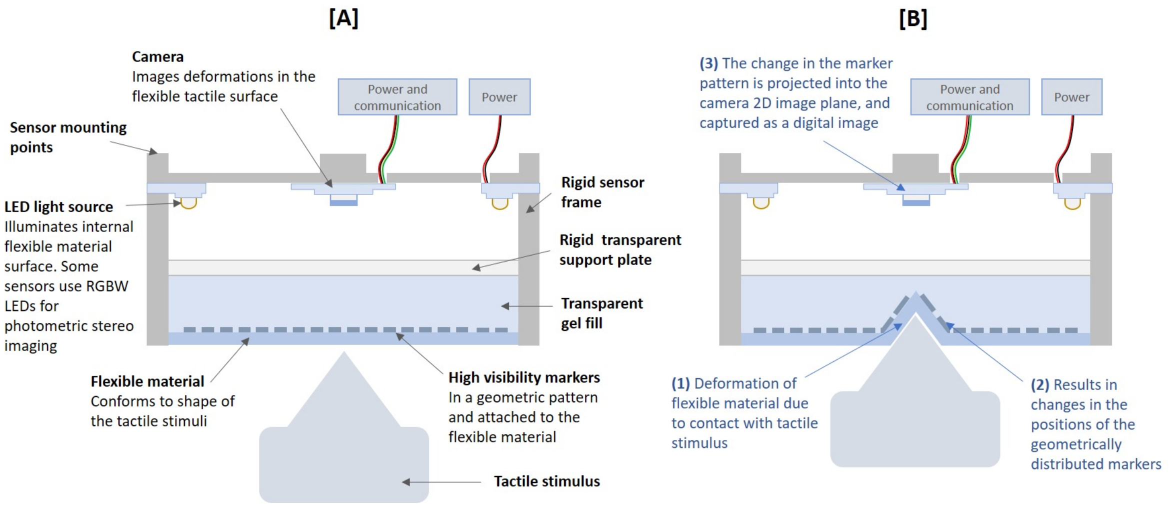

FIGURE 1.2. Cross section of a typical optical tactile sensor. Illustrates architecture, and transduction working principal. **[A]** Sensor is not in contact with tactile stimulus. **[B]** Sensor is in contact with tactile stimulus. Figure adapted from [23] [24]

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.

CHAPTER 2

LITERATURE REVIEW

Significant research has been conducted in the field of tactile sensing [33] [16][3]. In recent years this has lead to to major advances in capability for the tactile transduction and perception pipeline.

The focus of this chapter is fingertip based tactile sensors, the robotic platforms they are commonly deployed on, and recent deep learning methods which are applied to achieve perception and action outcomes (Figure 1.1). The aim is to provide a description of the current state of the fingertip tactile research field, setting the context for this research. This thesis draws on this contextual backdrop for specific tactile benchmarks, with which the results from this research can later be compared.

Section 2.1 describes the technical importance of tactile perception for a high level robotic system. In Section 2.2, the operating principles of tactile sensors are illustrated and the design and applications of state-of-the-art optical based tactile sensors is discussed in detail. The application of deep learning methods to tactile sensing is then investigated in [HOLD, Section 2.3] and common patterns of the application of Neural Networks to manipulation problems are identified. The inclusion of tactile feedback in closed loop servoing tasks is surveyed in [HOLD, Section 2.4]. Finally, a review of robot manipulator platforms onto which tactile sensors are commonly deployed is presented in [HOLD Section 2.5].

2.1 Context

While manipulation tasks using robot actuators without touch feedback are widely found in both industrial settings and state-of-the-art research applications [34], it is widely acknowledged that tactile feedback is an important enabler for a human-like level of manipulation capability in robotic systems [3].

However tactile sensing also has clear limitations. Because touch is a proximal sense, it means that instantaneous sensor readings most commonly capture local features as a subset of a global object. A tactile sensor must have an initial estimate of the position of the object in order to initiate contact. Consequently common tasks like grasp planning are best executed when tactile sensing is fused with a distal sense, especially vision. Tactile perception is an invaluable input to a fused perception model.

'Robotics history' empirically demonstrates that improvements in accurate and reliable perception are a catalyst for significant robotics progress [22]. Examples of this are LIDAR spurring advancements in autonomous vehicles, and neural networks sparking advancement in computer vision and audition.

Mathematical fusion principles like Kalman filters demonstrate that even small amounts of additional information about a property of a physical environment (often termed a process) can vastly improve a probabilistic estimate of the true underlying value [35].

It is against this backdrop that the research surveyed in this literature review sits. Even incremental improvements in tactile sensing can have significant positive impacts for robotic system capability as an input into a fused perception model [36].

2.2 Comparison of tactile sensing and perception methods

Tactile sensing and perception in its most basic form consists of a transduction mechanism and a perception mechanism. It is common for the surface of the sensor to employ a compliant 'skin like' material which can conform to the shape of a tactile stimuli. The transduction mechanism converts the deformation of the flexible surface into an electronic signal. The perception algorithm extracts relevant features from the electronic signal and commonly uses a regression method to map these to desired outputs representing quantifiable physical descriptions of the tactile behaviour (for example: contact force, relative stimuli pose, shear force, slip). Understanding tactile sensing and perception is a crucial element in implementing tactile feedback in any robotic or autonomous system.

2.2.1 Transduction methods

Various physical principles have been used for the purposes of transduction in tactile sensors, where proximal contact with a tactile stimulus is converted into an electronic signal. The most simple type of tactile fingertip transduction mechanism can be categorised as *single point contact sensors*. Point features can be extracted from this type of sensor. These features can represent confirmation of contact with an object (e.g. by using a electronic limit switch), point contact size (e.g. by using conductive fluid encased in a soft shell [37]), point contact force (e.g. using a linear piezoresitive sensor [33]) or slip (e.g. using an accelerometer embedded in a fingertip manufactured with ridges [16]).

Transduction mechanisms which better mimic the human fingertips can be categorised as *high spatial resolution tactile arrays*. This type of mechanism permits differentiated tactile feedback over the surface of the tactile array, providing information about the location or type of contact. This is the predominant category of sensor used for tactile research [3]. There is a wide variety of examples of different high spacial resolution tactile arrays which have been described in literature. The smallest spacial resolution element of which the tactile array is formed is commonly referred to as a *'tactel'* [16].

The 'Takktile' sensor consists of customizable sized arrays of MEMS (Micro Electromechanical System) barometer elements which have been mounted on a solid printed circuit board substrate and encased in urethane [38]. This waterproof array design can be used to detect contact pressures and contact locations by sampling the signal from the array of barometers using a Analogue to Digital converter (ADC) [39].

The 'Biotac' fingertip sensor has been used extensively in academic research and has been commercialised. It consists of a flexible skin which encapsulates an incompressible fluid above an array of 23 electrodes mounted to a rigid substrate. Impedance changes in the electrodes allow contact forces to be detected. A pressure sensor can detect vibrations which manifest as pressure fluctuations in the incompressible fluid. A temperature sensor allows for object discrimination by detecting ambient heat flow [40][41].

A fiber optic high spatial resolution tactile array has been developed specifically for tissue palpation in medicine, where tissue texture is assessed by touch to detect anatomical landmarks or abnormalities. The sensor consists of an array of 12 tactels. Each tactel element is formed by a moving mirror attached to a flexible skin, which alters the path of light reflected through a fiber optic pair. This sensor detects contact force only in the z-axis and was shown to have a resolution of 0.05. This has been demonstrated as sufficient for medical use to detect tissue nodules. Importantly this sensor is compatible for environments where patients undergo Magnetic Resonance Imaging (MRI) [42].

Notably improvements in state-of-the-art transduction for high spatial resolution tactile arrays have recently culminated in widespread research use of *optical tactile sensors* (sometimes refered to as *Visuotactile Sensors*). At ICRA 2020 for the workshop "ViTac 2020: Closing the Perception-Action Loop with Vision and Tactile Sensing" four out of six accepted papers used optical tactile sensors for experimentation [20] [21] [43] [22]. The authors of [44] offer a comprehensive review of the development history of this specific sensor type.

Typically, this type of sensor contacts a tactile stimuli with a flexible material which is labelled with a geometric pattern of markers. This contact action causes the flexible material to deform in reaction to the forces that the stimulus exerts on the tactile sensor. The flexible material is imaged by a digital camera, such that the 3 dimensional deformation of the flexible surface is projected into a 2 dimensional image plane and captured as a digital image. The digital image can be compared to a reference image, which is taken when the sensor is not in contact with a stimuli. Changes in the digital image represent changes in the state of the tactile sensor, where the pixels in the image are equivalent to tactels. [HOLD, figure - example of one of the sensors]

There are a number of advantages associated with optical tactile sensors which has resulted in their widespread use in the tactile research community. These include:

- **Relatively high spacial precision and perception performance:** For the measurement of deformation of the tactile surface, as well as the desired perception outcomes (such as contact force estimation) [24].
- **Ease of fabrication and wiring:** Due to the separation between the optical sensor and the flexible material used to contact a tactile stimulus [24].
- **Leveraging technological improvements in digital imaging:** For which the reduction in cost and increase in capability of sensors (such as the CMOS sensor) continues to advance rapidly [45].
- **Synergy with deep learning and convolution neural networks for computer vision:** Every pixel in the captured 2D image contains information about surface deformation. The perception challenge is a mapping of features from this image plane into an output space. This is strongly analogous to deep learning for computer vision where neural networks have proven efficient at mapping non linear image features (for example lines and gradients) into an output space (for example face detection). This shared 'type' of neural network input means improvements in deep learning can be relatively easily adopted [15].

The distinct designs of different optical tactile sensors are closely linked with the perception mechanisms used to map features from the image plane into the output space. For this reason their transduction mechanism will be reported together with their perception method.

2.2.2 Perception methods for optical tactile sensing

Perception for tactile sensing is a mapping of extracted features from the transduction ouput to desired perceived outcomes (for example contact force, relative stimuli pose, shear force, slip). This mapping is often highly non linear due to the complex interaction of a flexible tactile surface with an object. The transduction output depends on a number of factors that are non-trivial to model such as contact history, and the low pass filtering effect of a compliant tactile surface [16]. Various modelling and statistical methods have been used to address this problem, the most effective methods are case dependant and necessarily depend on the desired perception outcomes. [3]

Notably the application of deep learning methods has improved perception results due to the inherent strengths of deep neural networks in modelling complex non-linear relationships. In this literature review examples are given of current state-of-the art optical sensor designs coupled with recent perception methods with which they have been deployed in research.

The TacTip [23] optical tactile sensor is developed at the Bristol Robotics Laboratory, and is used in this research project to provide tactile feedback. The TacTip is biomimetic in design, replicating how mechanoreceptors (Merkel cells) situated at the boundary of the epidermis and dermis of human skin work together with the intermediate ridges of the fingertip. In the human fingertip, Merkel cells provide sensory feedback on the pressure distribution resulting from a contact surface. In the TacTip sensor internal pins replicate the structure and behaviour of the Merkel cell complex when the flexible sensor skin contacts a surface. The modular nature and design principle of the sensor (camera imaging internal pins) means that the flexible skin can be shaped into a wide range of geometries. The first designs for the TacTip were conceived before the current "present revolution in AI:" [15]. Regardless, using deep neural networks for perception on the digital image data from the TacTip sensor has been shown to surpass accuracy and generalisability of other functioning tactile perception methods previously used (for example Maximum Likelihood Estimation) [46]. Deep learning for perception is applied by collecting training data for multiple contact poses between a tactile stimuli and the with the sensor. Training of a deep neural network is undertaken using standard stochastic gradient decent methods, using the mean-square-error (MSE) measure to minimise the difference between perception target labels (e.g. relative stimuli pose) and the predictions (on the tactile image input). The architecture of the deep neural network (described by hyperparemters) is important, and is optimised using a Bayesian optimization method. The TacTip sensor has been shown through quantitative testing to have high special resolution for localization (0.1mm) [15]. Furthermore, research using the TacTip sensor has demonstrated that this accuracy can be improved further for small scales when multimaterial 3D printing is used to created 'fingerprint like structures' that even more closely replicate the 'papillary ridge – dermis – Merkle Cell' structure [47] [48].

The GelSight [24] is another optical tactile sensor using a vision system (embedded camera and RGBW light sources) to capture useful information about changes in the geometry of a reflective flexible 'skin' when it is in contact with an object of interest. This has been used extensively in recent state-of-the-art academic research [49] [50]. The depth map captured by the GelSight sensor is built using photometric stereo imaging. This is undertaken by obtaining a series of separate photos whilst illuminating the reflective flexible skin with known changing light source orientation. The differences in reflected light intensity between each image are then analysed to calculate the constrained surface normal vectors. From this a depth map is built using a convolutional neural network [22]. The GelSight sensor has extremely high spatial resolution and has been commercialised as a tool to reveal material defects in the aerospace industry, by a company spun out of Massachusetts Institute of Technology [48].

A optical tactile sensor [51] using dense randomly distributed markers embedded in a flexible material has been developed to leverage the full resolution of the sensor camera. In this design *high visibility markers* (plastic particles) are distributed throughout the flexible sensor contact surface at varying depths. The optical sensor images any geometric changes in the flexible surface when it is in contact with an object. The optical flow of the particles is then calculated using standard computer vision methods. This 'averaging' effect over markers distributed throughout the flexible material means that the sensor accuracy is not limited by the number of sparse markers, but instead by the optical sensor resolution. When fed through a deep neural network, the transduction data output from this sensor has been shown to provide highly accurate contact force estimations [52]. These contact force estimations were shown to be similarly accurate if the deep neural network was trained using real world contact force data, or training data obtained from a finite element model [20].

The Digit [19] is a recently developed optical tactile sensor supported by 'Facebook AI', whose authors take much inspiration from the gelsight design then improve on it. The sensor uses the photometric stereo principle, but packages the sensor in a smaller (fingertip shaped) footprint than the gelsight. Most importantly the Digit is designed to be low cost (15 USD) and entirely open source such that CAD files, electrical schematics, manufacturing instructions and code samples are made publicly available for non commercial use. This is a marked departure from the more 'closed design' nature of other optical tactile sensors reported in literature and is likely to significantly reduce the barriers to academics studies seeking to incorporate tactile sensing into experiments. The authors demonstrate that the Digit is able to accurately estimate contact forces by undertaking a complex self supervised learning task on a Allegro robotic hand, where the robot must learn to manipulate a marble placed between two fingers to a desired position.

The Omnitact [53] is a multi directional, high resolution optical tactile sensor. It's authors are also supported by 'Facebook AI'. Whilst the Digit is designed to be low cost and open source, the Omnitact is designed to push the boundaries and capability of tactile sensing. Its design incorporates five micro cameras typically used in medical endoscopy, which are arranged so that there is a 360 degree field of view in the X-Y plane and a 270 degree field of view in the Z plane. This enables the authors to 'sensorize' the maximum possible surface area in a single sensor package. The electronics are assembled using a flexible PCB which is rolled into shape, then the transparent gel layer is cast directly onto the cameras in order to reduce sensor size. [HOLD, perception] The authors demonstrate that the benefit of a larger sensor surface area by undertaking an electrical plug insertion task where information sensed using the top camera and side camera is necessary to complete the task.

[HOLD] The rapid advancements in accuracy and generalisability made by the sensor-perception pipelines surveyed suggest that optical tactile sensing and deep learning will dominate as research themes for tactile sensing in the near term.

[HOLD] Looking to possible future research avenues, it is likely that the miniaturisation of cameras, light sources and optical tactile sensors will continue. Improvements in tactile perception, especially the generalisability of deep learning models used for this purpose continues to be an area of research. Processing time using deep neural networks can be addressed by ... careful neural network construction, input pre-processing... see [20]. Even so, a future direction of research may encompass hardware that permits deep learning models to be applied, custom hardware may be a future case, e.g. openCV embedded camera

[HOLD look at John Lloyd new paper via email - A Review of Tactile Information: Perception and Action Through Touch]

2.3 Closed loop control incorporating tactile perception

Once perceptual information has been extracted from the tactile sesnor's contact with the object, generally this is then acted on as part of a 'sense-perception-action' loop.

Deep

In addition to using deep learning for tactile perception, n

neural networks serve as a natural unifying framework for multi-modal signal fusion [from leporaOptimal ... need to change this because this is the exact text]

2.3.1 Material recognition

2.3.2 Contact force vector determination

[HOLD, reference biotac Dieter Fox paper for application of DL to contact force estimation in the deep learning section]

2.3.3 Tactile shape recognition and object pose estimation

2.3.4 combining vision and and touch for object perception

- Generalised force measurement using deep learning and the tactile sensor with 1000s of particles [Carmelo Sferrazza ICRA 2020 paper]

- object property perception for fabrics (Wenzhen Yuan ICRA 2020) - 3d force vector (Dieter fox ICRA 2020) [Self supervised learning] - object and contact is simulated in FEA (Dieter fox ICRA 2020) - rolling marble between two fingers (tactile sensors) [Roberto calandra ICRA] - Spacio-temporal model for texture perception [Shan Luo ICRA 2020 paper]

2.3.5 Something about training and datasets?

- There is a gelsight dataset from Wenzhen Yuan which i can find by looking in my gmail at the facebook digit comment - Simulation is usefull for this purpose -> sim to real transfer - Collect vision and touch concurrently allows better generalisation of models - Sim to real transfer -> [Carmelo Sferrazza ICRA 2020 paper] on FEA and simulated pinhole camera model - Some types of training are very resource intensive (e.g. reniforcement learning on the robot) with the digit sensor - Sim to real transfer -> peg insertion into hole with reinforcement learning [Fedor Chervinskii§ ICRA 2020 paper]

2.4 Tactile servoing methods

Many motor control tasks are better understood in terms of balancing of forces rather than joint positions. For robots it is very difficult to use vision alone to detect if a manipulator is initiating a successful grasp of an object. With tactile feedback, this becomes a much simpler problem, if for example the contact forces can be extracted and input to a closed loop tactile control system.

- hand grasping using tactile feedback (Peter Allen ICRA 2020) - Hand control using tactile feedback (Dieter fox ICRA 2020) -

2.4.1 Tactile servoing methods

2.4.2 Something about velocity and the other kind

2.5 Comparison of robot manipulator platforms

[Look at Nathan's latest papers (optimal)]. The development of the Digit (as possibly the first of many) low cost, open source tactile sensor(s) is a significant positive step in removing one of the barriers to increased application of deep learning to tactile sensors. The development of relevant public data repositories is breaking down another. The lack of interest in touch is gradually reducing as we see entrants such as Facebook, Nvidia suporting high profile researchers in this field. [15] But tactile robotics still lags behind computer vision, and the cost of robot platforms is still a barrier to the application of deep learning to tacticle sensing still faces significant research barriers such as [HOLD]. If the tactile sensor costs 15 USD but the robotic platform costs 15,000 USD there is still an issue.

- [HOLD, reference -> pick and place using cheap robotics platforms using deep learning (Sergey Levine - Vision-Based Multi-Task Manipulation for Inexpensive Robots Using End-To-End Learning from Demonstration)] [54]

2.6 FOR literature review

—- FOR literature review —-

The type and arrangement of sensory cells in the human hand results in perception of object properties being tightly linked to the motion of contact the hand is making with an object. 'Active exploration' using haptic sensing is an important human behaviour which helps us to identify "what" a physical stimulus is, and "where" it is relative to the human body. [2]

- sensor data depends on contact history!

Interestingly deep learning has been said to be more biommimetic than previously thought

- recently significant progress has been made in tactile servoing - the importance of tactile seroing is linked to active exploration and how humans manipulate objects

REMEMBER TO BE CRITICAL ! ! ! !

In the 2019 UK parliamentary report 'Automation and the future and work' the Business, Engergy and Industrial Strategy Committee calls faster UK adoption of robotics for applications in logistics, public relations and medicine. They comment that "the problem for the UK labour market and our economy is not that we have too many robots in the workplace, but that we have too few".

Some of the desirable characteristics of a robot platform for tactile sensing research are:

- Low cost
- High availability
- High reliability
- Suitable capabilities
- Appropriate form factor
- Ease of usability
- High confidence in performance due to known prior use
- Portability

CHAPTER 3

Implementation and modelling

Some new text

3.1 Section

Begins a section.

3.1.1 Subsection

Begins a subsection.

CHAPTER 4

BENCHMARKING TACTILE SENSOR ACCURACY ON AN INEXPENSIVE ROBOT ARM PLATFORM

The aim of this research project is to quantify the performance of a state-of-the-art tactile sensor on an inexpensive, lower capability robot arm (a 'Dobot Magician' robotic arm). Conclusions will be drawn by comparing this quantified performance to identical experiments undertaken on a higher capability platform which is commonly used for tactile experiments (a 'ABB [HOLD, add model]').

To achieve this goal, the robot is equipped with a biomimetic TacTip sensor as disclosed in [HOLD, ref implementation chapter.] The TacTip is used extensively in the application of haptic deep learning experiments by the Tactile Robotics Research Group at the Bristol Robotics Laboratory. These include: using deep learning to extract features to estimate grasp success using a robot hand [HOLD, ref], identifying objects when deployed on a manipuator [HOLD, ref], for the application of deep reinforcement learning [HOLD, ref], and to predict applied force and relative stimuli object pose.

Recent work has been focused on servoing for active exploration ... this represents state of the art. [HOLD, for the following reasons]. This work uses the 'ABB [HOLD, add model]'. The experiments conducted in this chapter, and chapter [HOLD] will aim to replicate aspects of this work, specifically in aim of achieving generalised tactile servoing along a 2D edge using a sliding motion.

[[HOLD, Flow chart] –> sensor in contact with surface -> image -> Deep neural network -> prediction of relative object position]

Active exploration using tactile servoing works by using the closed loop control principles outlined in [HOLD, reference closed loop control chapter]. The focus in this chapter is training and testing the deep neural network.

The role of the deep neural network in this control system is to accurately estimate the relative pose of a tactile stimuli in contact with the Tactip sensor. It represents the 'perception' element of the [HOLD , reference model from introductory chapter]

Adaption of this experimental method to suit a lower Degree of Freedom (DOF) platform represents a good opportunity for bench marking the performance of the TacTip tactile sensor using a deep learning on the Dobot Magician (as a inexpensive, lower capability platform).

4.1 Method

The focus of this first experimental chapter is testing of a deep neural network model in an 'offline' setting. The training and testing method for the deep learning model is engineered to follow (as authentically as possible) the published method disclosed in the paper [HOLD] for tactile servoing along a 2D edge. Following the same methodology will allow the results from the same experiment undertaken on different robot arms (higher capability ABB, lower capability Dobot Magician) to be credibly compared. The trained deep neural network is subsequently used for experiments in [HOLD, ref next chapter]

Validation of a deep learning model is the process by which a trained neural network makes predictions on previously unseen 'test set' data. This data in a 'test set' is withheld from the 'training set' used by the stochastic gradient decent algorithm to adjust neuron weights in order to minimise output error. The predictions made by the neural network on the test data set are used to quantify the performance of the model. In particular these results allow us to quantify model error, model bias and model variance.

In the application of deep learning to tactile sensing, the offline accuracy of neural network model is important for more than one reason:

- **It's a strong indicator of how the model will perform on a real world task:** (i.e. a tactile servoing task). Greater prediction error in the model used for positioning will be implicitly linked to performance degradation in closed loop control.

- **It is the most accurate way to measure absolute positioning error:** because it is relatively free from the influence of uncontrolled nuisance variables, especially any physical positioning error of a tactile stimuli. This is extremely difficult to guarantee as error free at a sub-mm level due to the relative position of the stimuli and robot arm end effector, with the multiple stacking tolerances of components that link them (e.g base, arm linkages etc.).

- **The accuracy of the model demonstrates whether the Dobot Magician is accurate and repeatable enough to collect data:** Innacuracies in positioning of the Tactip sensor would manifest themsevlves as high variance or high bias in the results set. This is a rigerous test, because the robot arm is experiencing forces resulting from sliding contact with the tactile stimuli, and is required to execute repeatable movements demanded under this condition. If (for example) the positioning accuracy of the robot arm was decreasing over time due to temperature effects from motor heating, this would be apparent in the results (see experiment setup for details).

4.1.1 Experiment 1: Training a tactile deep neural network for pose estimation

4.1.1.1 Experimental setup

The experimental setup is prepared to collect accurate, repeatable results. The Dobot Magician is screwed to a perspex mounting plate using the threaded mounting holes in the robot arm base. This perspex base plate is securely screwed to a perspex base plate, which contains a 25mm grid pattern of threaded mounting holes. Since a 3D model for the Dobot Magician arm is available, and since the perspex base and mounting plates are laser cut, then all relative dimensions are know. This base plate is engineered to fix the tactile stimuli in know positions relative to the Dobot Magician mounted Tactip. All other physical details are as described in [HOLD, ref implementation chapter].

The arm is controlled by, and data is collected on a 'relatively low specification' laptop with model [HOLD, Acer xx], which has no seperate GPU and therefore undertakes all processing using the ... chip. The software implementation is as described in [HOLD, ref implementation chapter]

4.1.1.2 Data collection

Three data sets of 2000 contacts were collected for sliding motion along a straight edge. To collect each data point, the Tactip is moved in a random motion to a known final position in contact the straight edge. An image is stored and labelled with the relative pose of the stimuli. Both the motion and known position are randomly sampled from a uniform distribution over the ranges disclosed in [].

The purpose of executing a random sliding movement before a tactile data point is collected, is to mimic the effect of motion on the tactile data. This is because in sliding servoing tasks, motion-dependent shear affects the measurements taken by the Tactip and similar optical tactile sensors as described by [HOLD, reference]. Incorporating these same movements into data collection ensures the deep learning model extracts features which are independent of these kind of shear effects.

A circular 'disc' stimuli is used for data collection, where the tactip moves peprpendicular to the edge, and collects data in positions along the x-axis as defined by [HOLD, reference figure to be created below]

[HOLD, digaram of birds eye (plan) view of circular disc with tactip sensor and relative dataframes]

Data is pre-processed as described in [HOLD, references]. Each tactile image is cropped and downsampled from a [HOLD, initial pixel size] pixel to a 128x128 pixel image. An adaptive threshold method is implemented in OpenCV to produce a binary black/white input to the deep neural network.

The data set which is designated for 'testing' is obtained immediately after the two data sets used for training. The time duration of breaks between sets of data collection are minimised (less than 5 minutes). This is to ensure that any inaccuracies induced by time dependant effects (especially heating of components like motors) are properly captured during the results, as these will effect real world performance during tactile servoing.

4.1.1.3 Deep Learning Model

The deep convolutional learning model architecture used in this experiment is described in recently published work and is coined 'Posenet' [15]. The consistency of the architecture for the neural network is paramount when comparing output results. From now forward, this deep convolutional neural network will be referred to as Posenet, consistent with .

Posenet is a proven architecture for accurate pose estimation using a Tactip sensor. The hyperparameters for this architecture are optimised using Bayesian optimization method [HOLD, reference] on a validation data set. This implements a systematic search for the optimum architecture over a defined (hyperparameter) search space. To reduce overfitting and variance in the output, this architecture includes regularisation coefficients as a optimised hyperparameter. To increase the generalization of the model to new mesaurements, early stopping on a validation data (sub) set is inlcluded as a optimised hyperparameter. The resulting architecture is detailed in table [HOLD].

The data sets for training contain a series of 2000 pre-processed tactile images (inputs), which are labelled with a euclidean relative pose (target). Training of the neural network by stochastic gradient decent was undertaken, using the mean-square-error (MSE) measure to minimise the difference between target labels (relative pose) and the predictions (on the tactile image input).

4.2 Results

The performance of the Posenet is assessed on the test set of data, containing 2000 labeled poses, collected in an identical manner to the training data set. Because it has been shown that Posenet can achieve sub milli meter accuracy for this task when used with the ABB [HOLD, model] robot arm, observed differences in the accuracy of the results can be linked to the Dobot Magician performance.

The performance is measured using mean absolute error which is defined as ...

The results are plotted over the data input space so they can be visualised

They are compared to identical experiments

Also show for the z axis

4.3 Discussion

Performance of the dobot magician is suprisingly good

Reflection that the mean absolute error for demanded trajectories is low. This is true for the x and inferred for the y axis. But also the z axis shows good results.

Lower DOF , less actuated joints, means that there is less room for stacked tolerance error.

—- For next chapter —

The hyperparameters for this model are set using baysian optimisation [as detailed in ...] . These are unchanged, with the exception of the number of filters, which is reduced from 512, to [HOLD] to improve the performance of the model

CHAPTER 5

Comparing tactile sensor performance using low level control on an inexpensive robot arm platform

Tactile servoing refers to ...
It is state of the art because ...
Using tactile deep learning is with the biomimitic TacTip is particularly effective to eliminate the motion dependant shear as a feature which can complicate implementation of this problem.

In this chapter, tactile servoing is undertaken using the 'lower cost, lower capability' Dobot Magician robot arm. The results are compared to identical experiments undertaken on the ABB

It is emphasised that although implementation for a new robot arm was required in preperation for this experiment, that the experimental results are a valueable academic contribution because they will be informative about decisions for future research with lower capability robot platforms, with their generalisation to other robot arm platforms plausable for the reasons given in [HOLD, reference talk about direct connection servos.] The results will depend on a large number of variables, the outcome of which is difficult to quantify without experimental investigation. These variables include:

- Temperature dependant effects - Backlash in gears - (look up other things in robotics fundamentals report) - Latency in the control of the arm

The deep neural network, 'Posenet', which has been trained using the dobot magician will be used as the perception layer in a tactile control scheme to enable servoing around a tactile stimuli, emulating active exploration.

5.1 Method

The method for this experimentation follows published results from ....

Chapter 6

TBD

Tactile ...

Chapter 7

Conclusion

Throughout this research, the main aim was...

APPENDIX

A

APPENDIX A

Begins an appendix

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