Copyright Statement

The digital copy of this thesis is protected by the Copyright Act 1994 (New Zealand).

This thesis may be consulted by you, provided you comply with the provisions of the Act and the following conditions of use:

- Any use you make of these documents or images must be for research or private study purposes only, and you may not make them available to any other person.
- Authors control the copyright of their thesis. You will recognize the author's right to be identified as the author of this thesis, and due acknowledgement will be made to the author where appropriate.
- You will obtain the author's permission before publishing any material from their thesis.

General copyright and disclaimer

In addition to the above conditions, authors give their consent for the digital copy of their work to be used subject to the conditions specified on the Library Thesis Consent Form and Deposit Licence.
Wearable Motion Capture Stretch
Sensors

Daniel Xu

Supervised by:
Associate Professor Iain A. Anderson
Professor Sheng Quan (Shane) Xie

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy at The University of Auckland.

The Biomimetics Laboratory
Auckland Bioengineering Institute
The University of Auckland
New Zealand

November 2015
Abstract

From improving our technique in sports to providing feedback for rehabilitation therapy, wearable motion capture sensors have the potential to greatly enhance and improve our lives. While traditional camera-based systems have limited usage outdoors, wearable sensors have the ability to follow us from our workplace to our homes, and continuously provide feedback on how we’re moving, anywhere and at any time.

One promising candidate for a wearable sensor is the dielectric elastomer (DE), a soft, flexible and highly stretchable polymer. In order to use DE sensors for motion capture, we need to be able to measure their capacitance, both accurately and efficiently. However, the large majority of low cost DEs have non-ideal electrode properties that cause problems for traditional capacitance sensing methods. Existing DE sensing methods were mainly developed for high voltage applications and lack the efficiency, safety and scalability to be implemented on a large scale, such as in a sensing suit.

This thesis addresses these sensing challenges. First, we present a new low voltage hardware design that can measure the capacitance of multiple DEs at the same time. Then, in order to reduce computational power, we discuss the design of an efficient capacitance circuit that can increase the monitoring period of the sensor by an order of magnitude. We also quantify, for the first time, how the sensing frequency can affect the accuracy of the capacitance measurement. This new model presents a new design guide on how to select a suitable frequency for any sensor design. Afterwards, we demonstrate the ability to sense local capacitance changes within the sensor. This breakthrough significantly helps to reduce the amount of wires, connectors and sensing electronics for large sensor systems, a key step for increasing the scalability of these systems. Finally, we extend our method for strain mapping into two dimensions, producing a soft touch keyboard.

The new low voltage capacitance sensing methods developed in this thesis are efficient, accurate and highly scalable. These improvements are key enablers that will allow DEs to be used as wearable motion capture sensors.
Acknowledgements

I would like to first acknowledge the person who got me started in this whole thing. Iain, thank you for coming down to the Engineering school four years ago and grabbing the attention of a young undergraduate student. We’ve had some memorable times together travelling to the SPIE conferences, touring NASA and catching the seals sunbathe on the rocks at La Jalla.

To my parents, whom ever since I was a child had prescribed that I had to do a PhD. Mum you can have my hat when I graduate. My sister Maggie, for making the figures in this thesis.

My co-supervisor Shane, for teaching me the technical skills I needed.

Silvain Michel, for bringing the large DE devices over to our lab and working together to solve the frequency mystery.

Ben O’Brien and Todd Gisby, I’ve always looked up to you both. I’ve seen you guys smash through your PhDs and then go on to start your own businesses. Thank you for inspiring me to do the same. For everyone else at StretchSense, thank for you making me feel like part of the family, I enjoyed all the picnics and BBQs.

Tom McKay and Andrew Lo, couldn’t have made all those SPIE demos without you guys, man we had some serious late nights working in the lab. In Tom we trust!

Shout out to all the guys at the Biomimetics Lab for making me eat a can of beetroot on my induction day. Auckland Bioengineering Institute. You have been my family. JJ Kim for teaching me how to make coffee in case I couldn’t finish the PhD and needed a job as a barrister. Andy Tairych for your precise hand that served as the force applicator in our experiments. Tony Tse and Daniel Chen for helping me make it back alive from the Yosemite’s. Alan Veale and Stacy Hunt, for convincing me to go to Cuba and almost getting kidnapped by a taxi driver.

Teresa Bates for your diligent work on editing my thesis. Thank for you teaching me about the difference between the US/UK spelling!

To the surf crew Marco, Chris, Markus (x2), Simon, Sammy for keeping me occupied over the weekends.

My flatmates Ben, Faisal and Markus for the fantastic flat dinners and proof readings of my thesis.
Finally to my business partners at Spark 64, Ming Cheuk and Richard McLean. Thank you for the patience and time for me to write this thesis. I look forward to spending the next chapter of my life working with you on new ideas that will change the world.
## Table of Contents

Chapter 1................................................................................................................................. 1

1.1. Camera-based motion capture ................................................................................................. 2

1.2. Sensor criteria .......................................................................................................................... 4

1.2.1. Accuracy and performance ................................................................................................. 4

1.2.2. Freedom and versatility ....................................................................................................... 5

1.2.3. Comfort and Safety ............................................................................................................ 6

1.2.4. Scalable for large numbers ................................................................................................. 6

1.3. Wearable sensor candidates .................................................................................................... 7

1.3.1. Fiber-optics .......................................................................................................................... 7

1.3.2. Inertial measurement units (IMU) ....................................................................................... 8

1.3.3. Liquid-metals ....................................................................................................................... 9

1.3.4. Ionic and hydrogels ............................................................................................................ 10

1.3.5. Piezoelectric sensors .......................................................................................................... 11

1.3.6. Piezoresistive fabrics and elastomers ............................................................................... 11

1.3.7. Piezocapacitive sensors (dielectric elastomer) ................................................................. 12

Chapter 2..................................................................................................................................... 14

2.1. Compliant electrodes .............................................................................................................. 16

2.2. Sensor designs and configurations .......................................................................................... 20

2.3. Current sensing methods ........................................................................................................ 24

2.3.1. Single capacitor model ...................................................................................................... 24

2.3.2. Series and parallel RC model ............................................................................................ 26

2.3.3. Combined lumped parameter model .................................................................................. 29

2.3.4. Transmission line model ................................................................................................... 33

2.4. Contributions of this thesis ...................................................................................................... 34

Chapter 3..................................................................................................................................... 36

3.1. Soft game controller ............................................................................................................... 37
7.3. Concluding remarks: to infinity and beyond................................................................. 90

7.4. Related publications...................................................................................................... 92

References ............................................................................................................................ 94
Table of Figures

Figure 1-1: Science fiction? A gesture controller featured in the movie Minority Report (adapted from [2]). Being able to capture our body motion is the first step towards more intuitive interfaces. .................................................................................................................. 2

Figure 1-2: Actor wearing light-reflective markers to track body position. This helps the CGI characters to move more realistically. ................................................................................................................................. 2

Figure 1-3: Camera-based systems are becoming more complex, often comprising of multiple cameras, lighting sets and green screens. These constraints limit their practical usage for outdoor environments. ........................................................................................................................................ 3

Figure 1-4: Wearable sensors should tolerate large degrees of motion from bending and stretching. 5

Figure 1-5: Traditional exoskeleton motion sensors used mechanical potentiometers to record angle rotation. These systems were generally bulky, heavy and obtrusive. .................................................................................................................. 5

Figure 1-6: Wearable sensors need to tolerate any unexpected falls or collisions and not harm the user. ........................................................................................................................................................................... 6

Figure 1-7: Recording hand gestures has traditionally been difficult due to the hand’s complex shape and high number of degrees of freedom. A scalable system is required which does not have significant bulk, weight or complexity. .................................................................................................................. 7

Figure 1-8: Fibre optic sensors measure strain by the modulation of light properties such as intensity, frequency, phase and polarization. (Adapted from [8]). .................................................................................................................. 8

Figure 1-9: IMUs measure point acceleration, orientation and inclination of different body parts using a combination of accelerometers, gyroscopes and magnetometers. .................................................................................................................. 9

Figure 1-10: Liquid-metal strain sensors contain a chamber of conductive liquid metal encapsulated in an elastomer shell. The change in the sensors’ resistance with stretch can be used to infer body motion. (Adapted from [25]) .................................................................................................................. 10

Figure 1-11: Ionic fluid sensors are highly flexible, stretchable and transparent. However, evaporation can be an issue if they are not properly encapsulated. (Adapted from [28]). ........................................... 11

Figure 1-12: Piezoresistive sensors made from conductive Polypyrrole can be integrated into clothing. (Adapted from [41])). .................................................................................................................. 12

Figure 1-13: DE sensors are soft, lightweight and stretchable, making them an excellent candidate for wearable motion capture sensors. (Adapted from [63]). .................................................................................................................. 13

Figure 2-1: (a) The DE is constructed by sandwiching a soft elastomer (dielectric constant, \(\varepsilon_r\)) between compliant electrodes (resistivity, \(\rho\)). (b) Its conventional lumped parameter electrical model consists of three strain-dependent terms \(C, R_s, R_p\). .................................................................................................................. 15

Figure 2-2: Conventional capacitance sensing ICs lack the ability to tolerate high, variable electrode resistance. Capacitive self-sensing techniques operate on high voltages and are not energy efficient.
The aim of this thesis is to develop low voltage capacitance sensing methods that are efficient, accurate and highly scalable. 

Figure 2-3: Adding clever patterns such as a corrugation profile can greatly increase the tolerated strain of metal thin-film electrodes without cracking. (Adapted from [49]).

Figure 2-4: Different types of carbon-based DE electrodes. (a) Direct deposition of carbon particles onto an elastomer. (b) Mixing the particles with a grease or oil binding agent to improve adherence. (c) Encapsulation into an elastomeric matrix for maximum bonding. (Adapted from [44]).

Figure 2-5: Electrical resistivity of common metal-based electrodes and that of typical carbon-based electrodes (coloured black).

Figure 2-6: Correctly measuring the capacitance of the DE requires accounting for the internal voltage drop ($V_{drop}$) across its electrodes ($R_s$). An error will occur if $V_{DE}$ is used instead of $V_c$. 

Figure 2-7: Motion such as rotation or flex can be captured by fixing DE sensors tightly onto the body and monitoring its change in electrical properties as a result of stretch.

Figure 2-8: Different deformation modes that can cause a change in the DE’s capacitance. Pressure, stretch and shear all cause a change in geometry. Proximity and touch use fringe fields and coupling effects. (Adapted from [55]).

Figure 2-9: A 6-axis, 3-dimensional DE sensor that can simultaneously detect forces and moments in different directions. (Adapted from [122]).

Figure 2-10: Interdigital finger patterns can be incorporated into the electrode to capture stray fields and increase sensitivity. (Adapted from [38]).

Figure 2-11: Two DE configurations with a large surface area that can provide insights into the challenges of a body sensing suit: (a) DE stack made from layering smaller discrete layers together (b) DE roll made from rolling a large sheet.

Figure 2-12: A matrix configuration with multiple nodes for measuring pressure in different regions. Multiple connectors and hardware channels are required. (Adapted from [95]).

Figure 2-13: The single capacitor DE model consists simply of a strain-dependent capacitor. As there are no resistive terms in this model, the measured voltage is the same as the capacitor voltage and the standard equation $Q = CV$ can be used to calculate the DE’s capacitance.

Figure 2-14: The change in capacitance can be measured measuring the shift in its cut-off frequency. Here, the frequency response of the DE has been shifted from the red line to the blue line by doubling its capacitance. (Adapted from [131]).

Figure 2-15: Two electrical models that account for the non-ideal resistive properties of the DE. (a) A series RC model to represent high resistance electrodes. (b) Parallel RC model which includes leakage through the dielectric membrane.
Figure 2-16: The DE’s resistance ($R_s$) and capacitance ($C$) can be determined from the gain and phase shift of the current from a sinusoidal sensing signal. .......................... 28
Figure 2-17: A typical self-sensing technique of superimposing a high frequency, low voltage sensing signal with a low frequency, high voltage actuation signal. The capacitance of the DE can be calculated after filtering the sensing signal and applying the gain and phase method (Adapted from [78]) .... 28
Figure 2-18: The combined lumped parameter DE model accounts for both the voltage drop across the electrode resistance ($R_s$) and the leakage current through the dielectric membrane ($R_p$). .... 30
Figure 2-19: The Hyper-plane method can be visualised by plotting the voltage (V), current (I) and charge (Q) of the DE in 3D space. Capacitance can be found by determining the projection of the plane of best fit in the Q-V axes [65]. .................................................................................. 31
Figure 2-20: (a) At low frequencies, the impedance of the capacitor approaches infinity, which causes it to drop out of the lumped parameter model. (b) Similarly at high frequencies, the impedance approaches zero, reducing the DE model to only its series electrode resistance ($R_s$). .................... 32
Figure 2-21: All three DE parameters can be deduced by performing an impedance frequency sweep on the DE and extracting features from the low frequency, high frequency and 3dB cut-off frequency response. (Adapted from [69]) ........................................................................ 32
Figure 2-22: The RC transmission line model assumes the DE is comprised of a distributed chain of smaller capacitors and resistors.................................................................................. 33
Figure 3-1: A traditional joystick controller is comprised of nothing but rigid components, which increases the risk of gaming injuries................................................................. 37
Figure 3-2: (a) A soft joystick controller comprised of DE sensors. Four sensing zones were used to measure motion in three axes. (b) Look up table for mapping capacitance changes to game controls. .................................................................................................................. 38
Figure 3-3: By designing the system to match the reaction speed of typical gamers, we could simplify the system by multiplexing the sensing signal and sharing the sensing hardware. ..................... 39
Figure 3-4: The OCTOSENSOR capacitance sensing circuit and specifications............................... 40
Figure 3-5: Testing DE sensor with a laser. The results showed a strong correlation between its capacitance and displacement.................................................................................................................. 41
Figure 3-6: Frequency response of a DE sensor when stretched from a state of 1nF to 2nF. Good sensitivity can be achieved when there is a distinct change in both the magnitude and the phase response....................................................................................................................................... 42
Figure 3-7: The DOOM controller: a gaming glove configured with DE sensors to detect hand gestures for playing video games. [Side note: a significant amount of time was spent ‘testing’ this device]. .. 43
Figure 3-8: The current integration method integrates current to determine charge on the DE. After approximately 3 RC time constants ($\tau$), the capacitor voltage ($V_C$) equals the supply voltage and the DE’s capacitance can be calculated using $3-3$.................................43

Figure 3-9: The area under each curve represents the charge on the DE for the normal and stretched states. If the sensing voltage is held constant, the difference in charge is directly proportional to the change in capacitance.................................................................44

Figure 3-10: (a) Sample circuit for the demonstration of charge tracking. (b) Charge tracking profiles for two different series resistances. After an initial transient stage, the charge on the DE quickly reaches the same magnitude as the capacitance of the DE. As the DE is stretched and relaxed, the charge tracks these changes in capacitance........................................................................................................................................45

Figure 3-11: Charge tracking analog capacitance output circuit. The entire capacitance sensing is implemented in hardware..........................................................46

Figure 3-12: The charge tracking method offers a similar performance to the computationally intensive Hyper-plane method.........................................................................................................................................46

Figure 3-13: Top: DE sensing glove to provide visual feedback for hand gestures. This can be used for controlling machines and non-verbal communication. Bottom: A hand gesture based video game controller for playing the video game DOOM.........................................................47

Figure 4-1: A DE of approximate size of 10 cm by 10 cm measured a capacitance of 1.756 nF at a sensing frequency of 120 Hz. (Measurement by Tenma 72-960 LCR meter)..............................................................................49

Figure 4-2: The same sensor measured a different capacitance of 1.539 nF at 1 kHz..........................49

Figure 4-3: (a) Two large DE stacks from EMPA [117]. These stacks contained a significant number of layers, which amplified the effect of a distributed electrode. (b) The stacks were constructed by layering alternating electrodes and dielectric material. A connection bus made from conductive carbon grease runs down the sides to bridge the alternating layers..............................................................50

Figure 4-4: (a) Four large DE rolls made by wrapping a single DE sheet around a spring core (Manufactured by EMPA [147]). (b) Construction of the roll starts from a large DE sheet tightly turned against a compressed spring.................................................................51

Figure 4-5: Measurement setup with a LabVIEW interface to calculate capacitance from the raw voltage and current signals........................................................................................................51

Figure 4-6: Stack 1 and 2’s capacitance frequency sweep with the Hyper-plane algorithm. Both the stacks’ capacitances seemed to decrease with frequency.................................................................52

Figure 4-7: A similar decrease was observed with the current integration algorithm..........................52

Figure 4-8: Capacitance of four DE rolls measured using the Hyper-plane method..........................53

Figure 4-9: Similar behaviour occurred with the current integration method..................................53
Figure 4-10: With a 1 kHz square wave sensing signal, the capacitor voltage ($V_c$) has adequate time to reach the supply voltage, allowing $V_s$ to be used in the calculation of capacitance......................... 54
Figure 4-11: The corresponding current response. Current exponentially decreases to zero as the system becomes fully charged. This signals that the total capacity of the DE has been sensed........ 54
Figure 4-12: A 5 kHz sensing waveform with the period now significantly reduced. The voltage drop caused by the electrodes can now clearly be observed. This shows that the system has not reached steady state.......................................................................................... 55
Figure 4-13: At 5 kHz, only a partial amount of charge was transferred to the DE. Hence the current integration method will under represent the capacitance of the DE.................................................. 55
Figure 4-14: (a) The ideal stack is simply a network of parallel capacitors. (b) A stack with a high electrode resistance ($R_s$). (c) The actual stack contains both electrode resistance and interconnect resistance terms ($R_c$). This model has no lumped parameter equivalent.............................................. 56
Figure 4-15: Distributed model of the DE stack. A total of 1433 segments were modelled, one for each DE layer. The connection terminals were located at one end of the chain, thus creating a transmission line effect.................................................................................................................................................................................................. 57
Figure 4-16: Impedance simulation of the stack’s distributed models for different interconnect resistance values. .................................................................................................................................................................................................................................................. 57
Figure 4-17: Capacitance frequency simulation of the distributed transmission line model for different interconnect resistances. .................................................................................................................................................................................................................................................. 58
Figure 4-18: The lumped parameter impedance of the DE consists of a resistive part ($Z_R$) and a capacitive part ($Z_C$). These show up independently as the real and imaginary terms in its impedance. ........................................................................................................................................................................................................................................ 59
Figure 4-19: A two chain section of the DE distributed model. $R_s$ and $C$ represent the electrode resistance and capacitance of each individual DE, respectively. $R_c$ is the interconnect resistance between each layer. ........................................................................................................................................................................................................................................................................................................ 59
Figure 4-20: The capacitance of a two segment distributed model and its coercion under a lumped parameter assumption. All of these circuits have the same electrical impedance. ......................... 60
Figure 4-21: The rolled configuration resembles a planar DE with a large aspect ratio. The extreme length amplifies the distributed effects of its high resistance electrodes............................................... 61
Figure 4-22: Voltage readings at various locations on the DE’s electrode. Here we that the 10 Hz and 100 Hz signal causes a different voltage. The lumped parameter condition is met if the voltage is uniform throughout the entire length of the electrode................................................................. 62
Figure 4-23: (a) The mechanical response needs to be sampled with a fast enough sensing signal to prevent aliasing. (b) Once a minimum sensing frequency satisfying the Nyquist sampling criteria has
been determined, it should be tested against the capacitance frequency response to ensure that it does not violate the lumped parameter sensing assumption.  

Figure 5-1: The challenge of using DE sensors in touch keyboards is that the sensing methods are based on a lumped parameter model. This means that for every new key, we require another sensor (and wires, connectors and sensing electronics).  

Figure 5-2: The transmission line electrical model can be used to analyse the internal response of the DE as a function of length (z). The parameters ($R'$) and ($C'$) represent the resistance and capacitance per unit length, respectively. The inductance ($L'$) and leakage ($G'$) can be ignored for short lengths and low sensing voltages.  

Figure 5-3: A DE can be reduced to its constituent capacitors. Measuring the capacitance of these individual sections is the key to detecting local deformations such as a finger press.  

Figure 5-4: (a) At low sensing frequencies, the internal voltage is uniform along the length of the DE. (b) As the input frequency is increased, the voltage suffers attenuation. (c) This effect can be reversed by reducing the resistance of the electrodes.  

Figure 5-5: Lower sensing frequencies are sustained longer in the transmission line and are thereby able to measure a greater proportion of the total capacitance. By comparing the capacitance measured at different frequencies, we can thus determine local changes in capacitance.  

Figure 5-6: The lumped capacitance difference at two different frequencies indicates the number of capacitors between these two sections.  

Figure 5-7: A single DE sensor split into four sensing regions to represent different notes on the keyboard.  

Figure 5-8: A frequency sweep was used to determine the level of reach for each sensing frequency. The total capacitance of the DE was around 220pF.  

Figure 5-9: Four different regions marked on the DE keyboard. The sensor was fixed into a plastic frame to isolate deformation to the specific sections.  

Figure 5-10: Four sensing frequencies were combined and simultaneously sent to the DE keyboard. A band pass filter was used to decompose these frequency components for calculation of the corresponding capacitance. Finally, a matching algorithm was used to compare against a threshold value to determine which note to play via the loudspeaker.  

Figure 5-11: Capacitance frequency response of single and multiple presses. We used the high frequency components to determine which key was pressed, and the low frequency component to determine how many were pressed.
Figure 5-12: Pressing locations further down the transmission line shows a lower change in capacitance. A simple threshold could be used to identify which key was pressed. Note, only a single pair of wires were used to sense the four different regions.

Figure 5-13: The capacitance frequency profile can be lowered by using higher resistance electrodes, pushing the curve to the left.

Figure 5-14: Additional ground electrode layers can be added to shield the sensor from environmental noise.

Figure 6-1: A DE sheet can be made into a sensing skin to cover large areas of the body. By sensing local capacitance changes in the sheet, we can determine where the deformation is happening.

Figure 6-2: (a) Traditional multi-sensor approach where each sensor is packaged as a discrete unit with its own set of wires. (b) The new transmission line method can serve the same function by using localized capacitance changes within the same sensor to infer different positions. Only a single set of connectors is required.

Figure 6-3: The RC transmission line model consists of an infinite chain of resistor and capacitor segments, each of which acts as a low pass filter. High frequency sensing signals are attenuated as they travel into the electrode and are thus unable to measure capacitors which are further away.

Figure 6-4: The sheet was constructed with 5 layers of alternating electrode and PDMS dielectric. The electrodes were placed at a 90 degree angle to create two separate transmission lines in their respective directions.

Figure 6-5: The frequency response for both sensing layers showed a similar decrease in capacitance with frequency due to transmission line attenuation.

Figure 6-6: Sequentially sweeping through each sensing frequency can be slow and susceptible to time lapse errors. A solution is to measure all frequencies at the same time using a Fast Fourier Transform.

Figure 6-7: (a) Two separate sensing circuits were used to measure the capacitance of the X-layer and the Y-layer at multiple frequencies. (b) Cross sectional view: each layer was modelled as a separate RC transmission line in orthogonal directions.

Figure 6-8: Local deformation was manually provided to different parts of the sheet using a plastic shaft.

Figure 6-9: (a) Dividing the DE sheet into 4 quadrants. (b) The high frequency capacitance (red and blue) can be used to localise the position of the key press. The low frequency capacitance (green) shows a consistent press across all quadrants and can be used to infer the overall magnitude of displacement.
Figure 6-10: (a) The specific row can be identified by comparing the relative capacitance change in the Y-layer at all three frequencies. (b) A similar process can be performed on the X-layer capacitances to determine which column has been pressed. (c) Combining the row and column data allows the sheet to recognise nine distinct keys.

Figure 7-1: The motivation of this thesis was to develop wearable motion capture sensors so that we can freely and unobtrusively capture the incredible mobility of the human body. (Image from [156])

Figure 7-2: The vision is to enable a complete motion capture sensing skin to measure our motion anywhere and at any time (Image from [157]).
Introduction

Imagine you’re on the golf course and about to take a swing. *Ping!* You send the ball slicing off to the right. *Not again!* you exclaim angrily, hoping to have learnt from your earlier mistake. Imagine now that you’re a patient recovering from a back injury. The physio has prescribed a series of rehab exercises for you to try at home. The only problem is that you can’t remember how to do them correctly.

If only there was a way that we could measure and quantify our body motion anywhere and at any time. This information could help us to improve our technique and posture, control new machine interfaces and communicate with each other using body language. There is a vast amount of information encoded in how we move, from direct gestures to subconscious movements. In fact, over half of our non-verbal communication comes directly from our body motion [1]. Think of the last presentation you gave. Do you remember what your hands were doing? Imagine if we could record and interpret that information for the hearing impaired.

What if there was a way that we could capture all of our motion data from our daily life, freely and unobtrusively? This would include a range of activities from walking in the park to playing with our children and identifying our mood. Imagine being able to automatically share our excitement with others, or alerting a tired driver who’s fallen asleep behind the wheel. Motion sensing technology could completely change the way we interact with computers and mobile devices (Figure 1-1).
In this thesis, we aim to develop a wearable sensor technology that has the ability to record our body motion accurately and efficiently. But before we begin, let’s see what we can learn from Hollywood.

### 1.1. Camera-based motion capture

When it comes to motion capture, most people think of the reflective markers and cameras used to create computer generated imagery (CGI) in films such as *Avatar* and *King Kong*. Actors, whose performances the motion of CGI characters are based on, wear special light-reflective markers to track their joint positions using infrared cameras (Figure 1-2). This forms the basis of a kinematic model which helps to make the CGI characters move more realistically. Over the years, Hollywood has pioneered much of the technology in this industry and is often considered the gold standard.
One advantage of a camera-based system is that the markers are small, lightweight and unobtrusive. Bulky equipment such as cameras, lighting systems and processing computers are stationed around the user. This separation allows the user to move as freely and naturally as possible. Newer markerless systems take this even further by not requiring the user to wear any attachments and using computer vision to analyse the subject’s motion [3], [4].

Another benefit of camera-based systems is their high accuracy, sample rate and precision. High resolution cameras can capture up to 120 frames per second. Unfortunately, as camera-based systems have evolved from a single camera to complete studios, there has been an exponential rise in setup costs [5] (Figure 1-3). It seems inevitable that the gold standard of motion capture will soon turn into a diamond one.

![Figure 1-3: Camera-based systems are becoming more complex, often comprising of multiple cameras, lighting sets and green screens. These constraints limit their practical usage for outdoor environments.](image)

Coupled with the rising cost is also an increase in complexity. Apart from the large number of components to set up, camera-based systems typically require a factory of computers to process and filter the data. This step is very computationally intensive, making real-time feedback difficult to achieve [5], [6]. The large amount of supporting equipment also takes up a great deal of space, reducing the portability of these systems. This leads us to the primary limitation of camera-based systems.

With so many parameters to control, camera-based systems are seldom used outside of the studio. This prevents their use in many real world settings such as the home, the workplace and outdoor environments. One concern when attempting to emulate these environments in the studio is a lack of authenticity. The studio is devoid of the environmental and emotional triggers that affect how we
move in real life. This is one of the reasons why figure skaters perform differently in front of a thousand spectators than in private training.

Another concern with cameras is privacy. The large amount of equipment is hardly inconspicuous. Imagine using them in a hospital setting. This could, on paper, help clinicians gather valuable data to track patient recovery. However, since cameras would also capture everyone around the subject, such an approach fails to distinguish ‘opt-in’ patients from everyday visitors. Even patients who have given consent may feel uncomfortable and move unnaturally, thus defeating the purpose of the task. This calls for a more discreet approach to motion capture.

For all their benefits, the lack of subtlety and limited versatility are two fundamental constraints that prevent camera-based systems from extending into our daily lives. From our day to day journeys, to our homes and our workplace, our lives could be greatly enhanced if we could measure our motion anywhere and at any time. This leads us onto the research objective of this thesis. **How can we measure human body motion as freely and unobtrusively as possible?**

The solution calls for a motion capture system that is discreet enough to run in the background, does not interfere with our movements and is versatile enough to operate in a wide range of outdoor environments. One solution is a wearable motion sensor. Such applications involve placing sensors on our body which can sense changes in our motion. These systems need to be accurate, non-obtrusive, comfortable to wear and scalable for large numbers. The next section discusses these goals in more detail.

### 1.2. Sensor criteria

#### 1.2.1. Accuracy and performance

The first aspect of the requirements for wearable motion sensors relate to how well they can measure motion. While a high degree of accuracy is important, three other requirements should also be considered. First, the readings of the sensor need to be repeatable. This is particularly important for rehabilitation programmes, where data may be collected over a long time. Hence, it is important that changes in sensor readings reflect actual changes in the motion of the subject, and are not a result of drift over time. Second, the sensor needs to have high enough resolution to allow small movements such as breathing to be measured. Finally, and perhaps most importantly, the sensor needs to tolerate a large range of motion. As the human body is highly agile and flexible, it is easy for sensors to be damaged. Sensors tightly coupled to the body are particularly vulnerable, as they are likely to undergo large changes (Figure 1-4).
1.2.2. Freedom and versatility

Prior to the development of camera systems, motion capture systems were of a mechanical nature (Figure 1-5). These systems were typically bulky, heavy and generally obtrusive. Wearing them usually altered the subject’s centre of mass, aerodynamic drag and often interfered with their movements. Thus data recorded was often not representative of the subject’s natural motion. Rather than restricting the wearer, a motion capture system should allow them to move as freely and naturally as possible.

When improving the user’s freedom, we also need to take account of the social stigma that may result from wearing bulky sensors. Recently this was experienced by people wearing Google Glass, an augmented reality headset with video recording functionalities. Users reported abuse and
discrimination as a result of wearing the headsets in public [7]. If wearable motion sensors are to be integrated into our lives, then they need to offer a level of discretion so that they can be hidden.

Finally, the sensors need to have the freedom to operate in a wide range of outdoor environments. As previously discussed, this was the primary limitation of camera-based systems as they were nearly always constrained to a studio. A portable system would need to tolerate a range of conditions including changes in temperature, wind and humidity.

1.2.3. Comfort and Safety

The tolerance of a range of conditions should not compromise the user’s comfort. This is important because a sensor that is uncomfortable or intrusive will suffer poor usage compliance, resulting in the loss of valuable data.

Since our bodies are naturally soft and flexible, a wearable sensor will experience better coupling if it has similar properties. By integrating sensors unobtrusively onto our body, they can function in the background without drawing attention to themselves. They also need to have a certain degree of robustness to survive any falls or collisions (Figure 1-6). This safety consideration extends beyond the sensor to the wearer: the sensor must not cause the wearer any injury.

![Figure 1-6: Wearable sensors need to tolerate any unexpected falls or collisions and not harm the user.](image)

1.2.4. Scalable for large numbers

Finally, the sensor needs to be scalable so that a large number of sensors can be attached to the body. As we are capable of a wide range of motion, we need many sensors located at different parts of the body to distinguish between different movements. While camera-based systems were able to increase their resolution by attaching more reflective-markers to the body, wearable sensors will
encounter the specific challenges of increased wiring, sensor cross-talk and limited computational resources.

One part of our body that has a large number of degrees of freedom is our hand (Figure 1-7). This makes it particularly challenging to measure. We need to be able to include multiple sensors without significantly increasing bulk, weight or complexity.

Figure 1-7: Recording hand gestures has traditionally been difficult due to the hand’s complex shape and high number of degrees of freedom. A scalable system is required which does not have significant bulk, weight or complexity.

1.3. Wearable sensor candidates

There are many different wearable sensors that can be used to record human body motion. These differ in performance, cost and the complexity of fabrication. The next section investigates some of the most promising candidates such as fibre-optics, inertial measurement units, liquid-metals, ionic polymer-metal composites, piezoelectric, piezoresistive and piezo-capacitive strain sensors.

1.3.1. Fiber-optics

The first wearable sensor candidate is the fibre-optic strain sensor. Fibre-optic strain sensors are typically comprised of an optical filter such as a Fiber Bragg Grating (FBG) which reflects light of specific wavelengths, depending on the strain or bend angle (Figure 1-8). As their sensing principle is based on light, they have excellent electromagnetic noise immunity and corrosion resistance.
Figure 1-8: Fibre optic sensors measure strain by the modulation of light properties such as intensity, frequency, phase and polarization. (Adapted from [8]).

However, one drawback as a strain sensor is that they are also dependent on temperature [9], [10]. A wearable sensor attached to the body is likely to encounter large temperature variations, particularly during sport and exercise. However, temperature dependency can be calibrated using an additional temperature sensor and algorithm [9].

Another limitation is that while these sensors are flexible, they are not stretchable. Without the ability to stretch or compress, relaxation can create slack, which can interfere with motion. Thus the optic-fibres need to be tightly adhered to the body.

A final factor limiting the wide adoption of fibre-optic sensors in wearable applications is the high cost of associated circuits such as digital interrogators and optocouplers [10]. Although various techniques such as multiplexing and daisy-chaining can be used to reduce the number of components [10], these are still generally expensive and bulky [10], [11].

1.3.2. Inertial measurement units (IMU)

An affordable alternative is the inertial measurement unit [12]–[15]. Traditionally comprised of a separate accelerometer, gyroscope and magnetometer sensors, advances in integrated circuit technology have combined these into a single form factor. Today it is not uncommon for small 9-axis, wireless IMUs to be attached directly to the body (Figure 1-9). In terms of sensor resolution, they have been shown to detect joint rotation down to 0.3 degrees with an error of less than 0.05 cm [15]. They can also characterise walking gait with over 95% accuracy [16], which is adequate for most motion capture applications.
As their main sensor is based on acceleration, IMUs are not adept at measuring quasi-static motion such as body posture. In addition, because of the magnetometer, they are susceptible to interference from iron structures inside buildings [17], [18]. This ferromagnetic dependency also makes them incompatible with prosthetics or walkers [19], limiting their use in healthcare. Other drawbacks of IMUs are drift [20], [21], temperature dependency [22] and the use of intensive Kalman filters to combine different sensor readings together [20], [21]. This intensive calculation is difficult to implement on portable processors.

1.3.3. Liquid-metals

Unlike IMUs, which measure a large number of different parameters, liquid-metal strain sensors simply measure a change in resistance. These sensors are typically made from Galinstan encapsulated in a silicone housing [23] (Figure 1-10). The combination of a soft elastomer shell and fluid centre makes them both flexible and stretchable, giving the sensor a high degree of compliance. They have been demonstrated to withstand strains of up to 200% in length [24].
Figure 1-10: Liquid-metal strain sensors contain a chamber of conductive liquid metal encapsulated in an elastomer shell. The change in the sensors’ resistance with stretch can be used to infer body motion. (Adapted from [25])

Unfortunately, liquid-metal sensors are less accurate than IMUs [25] and exhibit a high degree of nonlinearity [24], [25]. The biggest challenge lies in their complex multi-stage fabrication process [23], [25], [26]. The liquid channels are typically less than 1mm thick [25] and the sensor itself is only a few millimetresthick [26]. Delamination and leakage can attribute to up to 40% of failure [27]. This makes liquid-metal sensors less robust as any slight damage will cause an end to the sensor’s life.

1.3.4. Ionic and hydrogels

Other types of liquid sensors include ionic polymer-metal composites (IMPC) and hydrogels. These usually contain conductive Na⁺ ions in a water solution. The sensors are usually highly flexible, stretchable and can also be transparent [28] (Figure 1-11). There are also a variety of sensing principles including measuring a change in polarization [29], capacitance [28], [30], resistance [30], or impedance [31]. However, these sensors are susceptible to evaporation if not adequately encapsulated [28]. Just like liquid metal sensors, slight damage could stop them from working properly.
1.3.5. Piezoelectric sensors

These sensors are made from materials that generate a small amount of electric charge when deformed. This allows the use of simple measurement techniques and enables direct interfacing with data acquisition units.

Buchberger et al. [32], [33] have shown that pressure localisation inside a piezoelectric sheet could be determined by using a high resistance electrode and measuring the diffusion rate of charge at the edges of the sensor. This reduces the number of different sensing channels required. However, although piezoelectric sensors are flexible, most do not offer the high level of stretch required for a sensing skin [34].

1.3.6. Piezoresistive fabrics and elastomers

Piezoresistive sensors include fabrics and elastomers (Figure 1-12) that experience a change in resistance when stretched. These are typically made by embedding conductive materials such as Polypyrrole [31], [35], [36] in a polymer substrate [37] or by spreading mixtures such as Wacker Elastosil directly onto fabrics [38]. This makes them lightweight, easy to integrate into clothing [37], [39] and stretchable to over 100% [40].

Like liquid metals, they are easy to interface across multiple channels [41] and can take advantage of sensing configurations such as the Wheatstone bridge [42]. They are also more robust than liquid-metal as they can still operate after recalibration if broken. However, they are strongly temperature dependent [37], [38] and highly nonlinear [38], [40], [42]. In addition, they suffer from hysteresis [40],

Figure 1-11: Ionic fluid sensors are highly flexible, stretchable and transparent. However, evaporation can be an issue if they are not properly encapsulated. (Adapted from [28]).
requiring a special algorithm to keep track of the state of stretch. They can also suffer from resistance drift if exposed to open air and long transient times, which make them ill-suited for fast movements such as hand gestures or controls.

1.3.7. Piezocapacitive sensors (dielectric elastomer)

A more reliable sensing parameter than resistance is capacitance. Capacitive sensors are generally more linear, and less susceptible to changes in temperature and humidity. While most capacitors are not soft or stretchable, an exception is the electroactive polymer dielectric elastomer (DE). Originally dubbed ‘artificial muscles’ for their comparable properties to biological muscle, DEs are well suited to human body applications.

They are constructed by sandwiching a soft dielectric membrane such as silicone between compliant electrodes. This configuration electrically resembles a strain dependent capacitor, which allows for superior sensing capabilities. They can also stretch well over 100%.

With low cost materials and a simple fabrication process, DEs can be made into a variety of shapes and designs, a benefit when it comes to fitting different body sizes. They have similar mechanical properties to piezoresistive polymer sensors so they can also be easily integrated into clothing or used as wearable attachments. This wide versatility has seen DEs used in a variety of applications from sensing skins, computer touch pads, healthcare, sports to structural health monitoring.
Figure 1-13: DE sensors are soft, lightweight and stretchable, making them an excellent candidate for wearable motion capture sensors. (Adapted from [63]).

With superior sensing performance, a high versatility to fit a wide range of body shapes and adequate comfort and subtlety for long term usage, DEs are one of the most promising wearable sensor candidates for the development of a portable motion capture system. However, as we will see in the next chapter, there are several core challenges preventing DEs from meeting their potential. These include the efficiency, accuracy and scalability required for large sensing systems such as the human body. This thesis aims to solve all of these challenges so that we can use DE sensors to capture human body motion anywhere and at any time. The next chapter reviews the current state of the art DE materials, configurations and sensing methods and outlines the specific research goals for this thesis.
The modern day dielectric elastomer (DE) was discovered in the 1990s by Pelrine et al. who created compliant electrodes that could remain conductive while being stretched up to 30% [47]. This major breakthrough far surpassed metallic strain gauges at the time which typically yielded over 2%. Their innovation involved the development of a new technique which used stencils to spray coat thin films of silicone and acrylic elastomers with powdered graphite and carbon particles. This gave birth to a class of soft, flexible and stretchable transducers.

It was also discovered that, upon application of a high voltage, Maxwell stress (a result of electrostriction) causes the membrane to contract in thickness and expand in area [47]. This created a push towards soft actuator devices. As they had similar properties to biological muscle [65], [66], a fast response [67] and the ability to sense pressure [47], [48], DEs were eponymously referred to as ‘artificial muscles’ [47], [68]. Over a decade later, this led to the development of a field of soft robotics, energy harvesters and wearable sensors.

At its core, the DE is a type of multi-functional electroactive polymer (EAP) [66] constructed by sandwiching a soft dielectric material between compliant, stretchable electrodes. This configuration naturally creates a soft capacitor whose capacitance is changed by deformation. It can be characterised by its lumped parameter electrical model (Figure 2-1), which consists of a variable capacitor and two resistive terms to represent the series electrode ($R_s$) and parallel membrane resistances ($R_p$).
Multiple strain inference methods have been developed, which include measuring the DE’s change in electrode resistance [46], capacitance [47], [48] or combined impedance [69], [70]. The first of these two parameters, resistance and capacitance are directly linked to the DE’s geometry by Equations 2-1 and 2-2, respectively. The other parameters in the equations are the resistivity of the electrode ($\rho$), the dielectric constant ($\varepsilon_r$) and the permittivity of free space ($\varepsilon_0 = 8.854 \times 10^{-12}$). While resistance is relatively easy to measure, it can suffer from temperature dependency [71]–[73], hysteresis [42], [74] and creep [46], [75]. Capacitance, on the other hand, is much more reliable since the dielectric constant is relatively stable and less susceptible to environmental effects [46], [48], [76].

$$R_s = \rho \frac{l}{tw}$$ \hspace{1cm} 2-1

$$C = \varepsilon_r \varepsilon_0 \frac{A}{d}$$ \hspace{1cm} 2-2

However, the challenge of using DEs as motion capture sensors is that capacitance is difficult to measure on a large scale as this requires special sensing hardware and algorithms. While there are commercial capacitance sensing integrated circuits (ICs), most are not compatible with low cost DE materials because of their poorly conductive electrodes [46], [75]. Therefore, in order to accurately measure capacitance, we need special methods that can account for the DE’s high, variable electrode resistance. Such methods have primarily been developed in the field of ‘self-sensing’, where the DE is simultaneously actuated and sensed [76]–[86]. Although these methods can accommodate highly resistive electrodes, they are usually coupled with bulky, high voltage electronics that lack the efficiency, scalability and safety required for motion capture applications. Figure 2-2 illustrates the deficient areas in DE sensing.
The aim of this thesis is to obtain accurate feedback for a large number of DE sensors so they can freely and unobtrusively capture our body motion. To achieve this, we require new low voltage capacitance sensing methods that are (1) efficient, (2) accurate and (3) highly scalable for large numbers.

The first point listed above covers the requirement of efficient energy consumption so that DEs can be used for a long period of time. It also addresses the need to efficiently manage resources to minimize space and weight. The second point addresses a problem that can occur in large DE designs with a highly distributed electrode such as in a sensing suit. The large size amplifies any non-ideal resistive characteristics which can interfere with the accuracy of the capacitance measurements [55]. Finally, as the human body has many different joints and degrees of freedom, we require methods that are highly scalable for measuring large numbers of sensors on the body.

This literature review is divided into three sections. First, we will learn why capacitance sensing for DEs can be challenging due to poorly conductive electrodes. Then, to understand how DEs can be incorporated as motion sensors, we will review different designs and configurations to increase their sensitivity. This will help us understand some of the practical challenges and limitations of DE sensors. Finally, we will review the different DE electrical models and methods to measure their capacitance. This will provide us with insights into how we can design more efficient, accurate and scalable sensing methods.

### 2.1. Compliant electrodes

The ideal electrode for a DE motion sensor is one that is highly conductive and stretchable. Maintaining a high electrical conductivity at large strains is an important requirement for good signal transmission and reliable sensors [87]. A high degree of stretchability is required to allow the sensor to undergo large deformations without constricting the natural movement of the user. The electrode
should not make the overall structure too stiff and should offer a certain level of compliance. This is a necessary requirement for user comfort and safety to ensure that no harm is inflicted in the event of a fall or collision.

As with most electrode choices, there is usually a trade-off between mechanical and electrical properties, availability and manufacturing complexity. Rosset et al. [75] categorised common materials for electrodes into two classes: metal and carbon-based electrodes. Metal-based electrodes are usually incorporated into DEs as thin-films [58], [88]–[90], ion particles [75], [91]–[94] and nanowires (AgNW) [50], [71], [95], [96]. These generally have a low resistivity of a few $\Omega/\square$ [88] (‘$\Omega/\square$’ symbolises “ohms per square”, the unit of sheet resistance). Amongst the best conductors are thin-films made from gold, silver and copper. These can be deposited directly onto Polydimethylsiloxane (PDMS) elastomers using techniques such as evaporation, electroplating, spin-coating and sputtering.

While the yield point of most metals is usually between 2-3%, DE researchers have found clever ways to obtain larger strains by using patterned designs [97]–[99]. One design by Benslimane et al. [100] consists of a corrugation profile (Figure 2-3) that allows the electrode to stretch up to 80% along the longitudinal axis [90].

![Figure 2-3: Adding clever patterns such as a corrugation profile can greatly increase the tolerated strain of metal thin-film electrodes without cracking. (Adapted from [49]).](image)

Larger strain can be achieved by directly implanting metal particles into the elastomer using a vacuum arc process [75], [94], [101]. Prof. Shea’s research group have used this technique with nanometre gold, palladium and titanium particles [94]. The group have achieved impressive strains of up to 175% and lifetimes of over 100,000 cycles [93], [94].

Equally high strain tolerance is achieved by electrodes made from silver-nanowires (AgNW). They typically have a sheet resistance of around 10 - 20 $\Omega/\square$ [102] and can be up to 80% transparent [103]. This makes them quite discreet if the user does not want them to stand out. They can also be screen printed [71] for mass fabrication.
While metal-based electrodes offer good electrical conductivity and moderate to high strains, they are generally expensive and require precise fabrication techniques. Therefore they cannot be mass produced for large-scale integration into clothing or wearable garments. A low cost alternative is the carbon-based electrode. Carbon black particles can easily be sourced in large industrial batches under commercial brands such as *Vulcan* and *Ketjenblack*. The ways in which they can be applied to electrodes are illustrated in Figure 2-4, and include directly scattering loose particles onto the membrane [104]–[106], mixing with a binding agent such as grease, and incorporation into an elastomer matrix. Unless properly encapsulated, carbon powder and grease can be messy to work with. They are subject to migration creep and mechanical abrasion [75], which reduces their lifespan.

**Figure 2-4**: Different types of carbon-based DE electrodes. (a) Direct deposition of carbon particles onto an elastomer. (b) Mixing the particles with a grease or oil binding agent to improve adherence. (c) Encapsulation into an elastomeric matrix for maximum bonding. (Adapted from [44]).

Carbon in the form of nanotubes (CNT) [50], [57], [60], [107], [108] is another type of electrode that offers impressive strain at low cost. Cohen *et al.* [57] demonstrated linear strains of over 100% with 3% variability over thousands of cycles. Similarly, Lipomi *et al.* [108] achieved strains of up to 150% with electrodes that were 79% transparent. This matched the transparency of the AgNW electrodes mentioned earlier. However, the resistance of CNT electrodes is also highly affected by stretch. Hu *et al.* showed that a 60% strain can cause a 20x increase in resistance [50].

Despite being relatively inexpensive, simple to make and capable of stretching over 1000% [109], carbon-based electrodes have the disadvantage of high resistance, often in the order of tens of kΩ/□ [24], [46], [110]. To make things worse, models have shown that the electrode resistance increases exponentially under uniaxial strain [77], making it difficult to account for. Figure 2-5 shows a comparison of the resistivity of several metals with that of some common carbon-based electrode materials.
A high strain-dependent resistance can cause problems for conventional capacitance sensing methods. To illustrate the reasons for this, we refer to the lumped parameter model for DEs shown in Figure 2-6. Internally, the electrode resistance \( R_s \) causes a voltage drop \( V_{drop} \) similar to a voltage divider. Unfortunately as this voltage drop is internal to the structure of the DE, we have no means of directly measuring it. A consequence is that we cannot use the measured voltage \( V_{DE} \) directly to determine the electrical charge on the DE since it is not equal to the capacitor voltage \( V_c \). Therefore, any calculation of capacitance based on \( V_{DE} \) without accounting for \( V_{drop} \) would produce an error in the result.

In summary, carbon-based materials can be used to make highly stretchable electrodes. They are of low cost, can be sourced in large commercial quantities and can be made using simple fabrication techniques. However, their high, strain dependent resistance can be a problem for conventional capacitance sensing methods. While there are developments which improve the electrical
conductivity of carbon materials [111], [112], the approach taken in this thesis is to develop robust capacitance sensing methods that can be adapted to accommodate their resistive properties, so they can be used on a large scale to measure our body motion. The next section examines some of the different sensor configurations available for achieving this aim.

2.2. Sensor designs and configurations

The human body is an incredibly mobile and dynamic system. In order to measure a wide range of motion from golf swings to subtle hand gestures, DE sensors need to be highly versatile so that they can be attached to different parts of the body. Common configurations include planar sheets [57], [89], interdigital fingers [113], diamonds [95], cones [114], [115], diaphragms [56], [116], stacks [69], [104], [105], [110], [117], [118], and rolls [48], [119].

The planar configuration is the most practical form factor for wearable sensors as it can easily be stitched over clothing or attached directly onto the body as a sensing skin. As with most wearable sensors, good mechanical coupling is vital to prevent slippage which is a main source of error [55]. Sensors typically need to be anchored around a stationary point such as an elbow joint to allow the natural rotation to compress or stretch the sensor (Figure 2-7).

![Figure 2-7: Motion such as rotation or flex can be captured by fixing DE sensors tightly onto the body and monitoring its change in electrical properties as a result of stretch.](image)

The five main deformation modes that cause a change in the DE’s capacitance are illustrated in Figure 2-8. For instance, shear is caused by a change in the overlapping area of the electrodes [70], [120]. Proximity and touch are related to fringe fields and coupling effects, respectively.
A limitation of the parallel plate configuration is that capacitance is linked to five different modes of deformation. Hence, we cannot use capacitance alone to differentiate between the modes. This is because both pressure and stretch decrease the DE’s thickness. Likewise, stretch and shear both alter the overlapping area of the electrodes. This indeterminacy can be resolved by having a prior knowledge of how the sensor will operate, or by monitoring other electrical parameters of the DE at the same time. Weigel et al. [121] managed to distinguish between pressure and proximity by simultaneously monitoring the change in capacitance with electrode resistance. Zhao et al. [34] designed their sensor so that finger proximity induced a much larger capacitance than pressing on the sensor. Alternatively, 3D designs with multiple capacitor arrangements [70], [122] can be used to measure multiple degrees of freedom at the same time. Kim et al. [122] used this idea to create a 6-axis sensor (Figure 2-9). Unfortunately, the design had a height of 7.5mm and so it would be difficult to integrate into a clothing.

**Figure 2-8**: Different deformation modes that can cause a change in the DE’s capacitance. Pressure, stretch and shear all cause a change in geometry. Proximity and touch use fringe fields and coupling effects. (Adapted from [55]).

**Figure 2-9**: A 6-axis, 3-dimensional DE sensor that can simultaneously detect forces and moments in different directions. (Adapted from [122]).
High resolution is an important specification for motion capture. The movements differentiating between good and bad walking techniques may only differ by a small margin. Hence, it is important that very small changes in capacitance can be measured accurately. However, for DEs these changes may be as little as a few pico-Farad, a level which could easily fall under the environmental noise floor. One way to solve this problem is to increase the sensitivity of the sensor by inducing a larger change in capacitance per unit force [114], [123]. Liu et al. [114] managed to achieve a sensitivity of 105 pF/N with a cone-shaped design. Others have added interdigital patterns [95], [113] to capture fringe capacitance and boost the sensitivity (Figure 2-10). Böse et al. [124] used both the fringe effect and a corrugation profile to further increase sensitivity.

![Figure 2-10: Interdigital finger patterns can be incorporated into the electrode to capture stray fields and increase sensitivity. (Adapted from [38]).](image)

Two configurations with both a high capacitance and high sensitivity are the rolled and stacked DE designs shown in Figure 2-11. Although these large configurations were originally made as high density robotic actuators and generators, the large number of distributed electrodes in their structure makes them a good case study for a sensing suit. Haus et al. [69] provide an electrical analysis of the stacked design with a distributed RC transmission line model and later simplified this to a lumped parameter model. In Chapter 4, we will show situations where this simplification can cause errors in the capacitance measurement and present strategies to overcome this problem.
Aside from the challenge of covering a large surface area, a sensing suit requires a large number of sensors to measure our motion in detail. One approach would be to place many sensors at different body locations. However, the approach is not scalable as each sensor comes with its own set of connectors, wires and sensing electronics. Techniques for simplifying this complexity have included reducing the number of wires using multiplexers \cite{125}, decoders \cite{54} and local capacitance converters \cite{126}. Many researchers \cite{34}, \cite{50}, \cite{58}, \cite{108}, \cite{127} have drawn inspiration from the semiconductor industry by employing matrix configurations (Figure 2-12). Matysek et al. \cite{127} managed to create a 10 x 10 grid using this approach. Choi et al. \cite{60} simplified this further by using a common ground electrode as one of the layers. However, like all other existing techniques, the matrix configuration still requires a separate connector and hardware channel for each sensing element.
existing designs require additional wiring, connectors and hardware channels for each new degree of freedom. This limits the DE’s scalability for motion applications that require a large number of sensors. Each of the methods developed later in this thesis is compatible with all of the configurations discussed so far. In order to understand them, we need to review the prior DE electrical models and capacitance sensing principles that form their foundation.

2.3. Current sensing methods

In order to use DEs to measure our body motion, we need to be able to accurately measure their capacitance. As we have already seen, most low cost DEs contain carbon-based electrodes which have a high, strain dependent resistance. While the conventional lumped parameter model shown in Figure 2-1 is generally regarded as the standard DE model, sometimes there are circumstances in which the resistive terms can be neglected without introducing significant error. We will review four variants of this model and the capacitance sensing techniques that have been proposed for each. Our aim is to gain insight into how they work so we can design new low voltage capacitance sensing methods that are efficient, accurate and highly scalable.

The four models:

1. Single capacitor model
2. Series and parallel RC model
3. Combined lumped parameter model
4. Transmission line model

2.3.1. Single capacitor model

The simplest DE model is a single strain-dependent capacitor (Figure 2-13). This model is used when the electrode resistance is low (e.g. metal films, particles or nanowires) and when the sensing voltage is low, so that the membrane resistance is typically in the order of $10^9 - 10^{12}$ Ωs [69], [110]. With no resistive terms in the model, measuring capacitance is relatively straightforward since the voltage of the DE is the same as its capacitive element. Thus we can use the natural capacitor charge-voltage relationship of Equation 2-3 to calculate the DE’s capacitance. Charge on the DE is usually determined by integrating its current [51], [123], [126], [128] (Equation 2-4) or by measuring the rate of change of voltage (Equation 2-5).
An advantage of a highly conductive electrode is that conventional capacitance sensing techniques such as *charge transfer*, *successive approximation* and *sigma-delta* can be used to calculate the DE’s capacitance. There are numerous commercial capacitance to digital converters (CDC) based on these techniques available. The CDCs frequently used by researchers include the *AD7152* [88], [89], [95], *AD7745* [125], *AD7746* [56] and *AD7147* [52], [120], [122]. These can have as many as 256 channels and more channels can be obtained by combining them with multiplexers [54], [125]. While most CDCs are simple to use and capable of a large number of channels, they were not designed for capacitors with high variable resistances such as DEs. They also lack the ability to customize their sensing frequency to match different DE sizes and thereby increase sensitivity.

Researchers have designed bespoke capacitance sensing methods to address this problem. For instance, Goulborune *et al.* [116], [129] modelled the electric field and discharge rate of the DE to determine its capacitance. Jung *et al.* [78] and York *et al.* [130] measured the output voltage by treating the DE as a high-pass filter (Figure 2-14) and detecting the change in the system’s cut-off frequency (Equation 2-6).
While the single capacitor model can take advantage of commercial capacitance sensing hardware, its adoption is limited to DEs with metallic electrodes. As these are generally expensive and require precise fabrication techniques, their usage in large-scale wearable sensing applications is limited. A more accommodating approach extends to low cost DEs made from carbon-based electrodes. For this approach, we require a model that can account the highly variable electrode resistance of these DEs.

2.3.2. Series and parallel RC model

To account for the resistive terms of some DEs, two electrical models have been proposed (Figure 2-15). These are a series RC model [66], [77], [78], [80], [84] aimed at representing DEs with a high electrode resistance, and a parallel RC model [67], [79] which represents any leakage current through the dielectric membrane. Much of the development of capacitance sensing techniques for these models was made through the field of ‘self-sensing’, where the DE is simultaneously actuated and sensed under high voltage.
Figure 2-15: Two electrical models that account for the non-ideal resistive properties of the DE. (a) A series RC model to represent high resistance electrodes. (b) Parallel RC model which includes leakage through the dielectric membrane.

Gisby et al. [82] used the series RC model with a current-controlled pulse width modulated (PWM) signal. This allowed the amount of charge transferred to the DE per cycle to be precisely determined. However, the method was implemented at high voltage under a quasi-static setting, which assumed a constant electrode resistance. Matysek et al. [127] extended this work by indirectly measuring the DE’s capacitance through matching its impedance against a reference capacitor in a Wheatstone bridge. Their method also assumed a constant electrode resistance. Keplinger et al. [80] noted that neglecting this variation in resistance could lead to significant errors. Goulborune et al. [116] addressed this problem by pre-calibrating the DE’s change in resistance with stretch in their model.

While all of these methods work under limited conditions, they struggle to measure dynamic capacitance changes in real time.

One way to account for the change in electrode resistance is to use a sinusoidal sensing signal and measure the current gain and phase shift (Figure 2-16). The complex impedance of the DE, $Z(j\omega)$, can be expressed by Equation 2-7. This is also the ratio of the input voltage to the output current given in Equation 2-8.

$$Z(j\omega) = R_s + \frac{1}{j\omega C}$$  \[2-7\]

$$\frac{V(j\omega)}{I(j\omega)} = Z(j\omega)$$  \[2-8\]

By measuring the transfer function gain ($G$) and phase shift ($\phi$), we can determine both capacitance and resistance by simultaneously solving Equations 2-9 and 2-10 [132].

$$G = \left| \frac{I(j\omega)}{V(j\omega)} \right| = \frac{\omega C}{\sqrt{1 + (\omega R_s C)^2}}$$  \[2-9\]
\[ \phi = \tan^{-1}\left(\frac{1}{\omega R_s C}\right) \]

The gain and phase method is typically used by many commercial inductance-capacitance-resistance (LCR) meters. A number of researchers have also used this technique to measure the DE’s capacitance [58], [70], [108], [113]. Keplinger et al. [80] was one of the first to implement a bespoke version of this method in a self-sensing DE by superimposing the sensing signal with a lower frequency actuation signal. Buchberger et al. [85] later repeated this setup to measure transient strain. Their method assumed that both the DE parameters \( R_s \) and \( C \) would remain relatively constant throughout the entire period of the sensing signal. However, no guidelines were reported on how to select an appropriate sensing frequency and the same frequency was used for all DE samples.

The gain and phase method was later widely adopted by self-sensing researchers [70], [72], [78]–[80], [85], [133] as it was a robust way to account for DEs with carbon-based electrodes. Many superimposed the sensing signal with a DC or triangle actuation signal (Figure 2-17) and used a high pass filter to later isolate the sensing component.

![Figure 2-16: The DE's resistance (\( R_s \)) and capacitance (\( C \)) can be determined from the gain and phase shift of the current from a sinusoidal sensing signal.](image)

![Figure 2-17: A typical self-sensing technique of superimposing a high frequency, low voltage sensing signal with a low frequency, high voltage actuation signal. The capacitance of the DE can be calculated after filtering the sensing signal and applying the gain and phase method (Adapted from [78]).](image)
While the gain and phase method accounts for electrode resistance by factoring out its effect on the current signal, a technique that accounts for the DE’s electrode resistance indirectly is the current integration method proposed by Matysek et al. [84]. This method integrates the charge current through the DE for a sufficiently long pulse width modulation (PWM) period, ensuring that adequate time has elapsed for the capacitor voltage to reach the supply voltage. This eliminates the associated voltage drop caused by the electrode resistance.

Unfortunately, choosing a sufficient PWM period requires knowledge of the time constant of the DE which is a function of the variables that the method itself attempts to determine. Thus some form of initial trial and error is required to choose a suitable sensing frequency. Nevertheless, current integration is a method with low computational intensity that has a high potential to alleviate some of the problems of processor overload. Despite the fact that the method was originally proposed for self-sensing using a high voltage PWM signal, we will present a low voltage adaptation of this method for use with a DC sensing signal in Chapter 3.

All of the capacitance sensing methods presented so far can also be adapted for the parallel RC model shown in Figure 2-15 in order to account for any current leakage through the dielectric membrane. Chuc et al. [79] used a similar gain and phase method, but adapted the DE impedance transfer function using Equation 2-11.

\[ Z(j\omega) = \frac{R_p}{1 + j\omega CR_p} \]  

2-11

The series and parallel RC models are useful simplifications in situations where the leakage current or electrode resistance can be neglected. These two models combine to create the conventional DE lumped parameter model.

2.3.3. Combined lumped parameter model

To enable DEs to be widely adopted as motion capture sensors, low cost materials with non-ideal properties should be included. A model that takes these limitations into account is the combined lumped parameter model [49], [66], [86], [134], [135] shown in Figure 2-18. By factoring in the resistive terms \( R_s \) and \( R_p \), we can more accurately calculate the DE’s capacitance. While the previously discussed methods were able to determine each of these terms separately, Gisby et al. [81], [83], [136] invented a least squares regression method that was capable of determining all three DE parameters simultaneously. This method was dubbed the ‘Hyper-plane approximation’.
The Hyper-plane method calculates capacitance by considering the total charge transferred to the DE \((Q_{DE})\). This is the sum of the instantaneous charge on the capacitor \((Q_C)\) and any leakage charge through the membrane resistance \((Q_{leakage})\) given by Equation 2-12, where \(Q_C\) can be expressed in terms of the general capacitor-charge relationship (Equation 2-13). Although we cannot directly measure the capacitor voltage \((V_C)\), we can express it as a function of the DE voltage \((V_{DE})\) minus the voltage drop across the series electrode resistance as in Equation 2-14.

\[
Q_{DE} = Q_C + Q_{leakage} \tag{2-12}
\]

\[
Q_C = CV_C \tag{2-13}
\]

\[
V_C = V_{DE} - I_{DE} R_s \tag{2-14}
\]

Substituting the value given by 2-14 for \(V_C\) in 2-13, we can express the charge on the DE as a function of its voltage and current as in Equation 2-15. Gisby et al. [81] noted that this equation resembles a typical plane in 3D space \((Q, V, \text{and } I)\), where determining capacitance is akin to finding the projection of the plane of best fit onto the charge-voltage axes (Figure 2-19). This can also be mathematically expressed in Equation 2-16 as finding the partial derivative of charge with respect to voltage \(\left(\frac{\partial Q_{DE}}{\partial V_{DE}}\right)\).

\[
Q_{DE} = CV_{DE} - CR_s I_{DE} + Q_{leakage} \tag{2-15}
\]

\[
C = \frac{\partial Q_{DE}}{\partial V_{DE}} \tag{2-16}
\]
Figure 2-19: The Hyper-plane method can be visualised by plotting the voltage (V), current (I) and charge (Q) of the DE in 3D space. Capacitance can be found by determining the projection of the plane of best fit in the Q-V axes [65].

Rizzello et al. [72] later showed that fitting the plane using the Recursive Least Squares (RLS) method was more accurate than using the standard Least Mean Squares (LMS) method, achieving an error term of less than 2%.

Aside from factoring in both the series and parallel resistances of the DE, a main core benefit of the Hyper-plane method is that it takes averages of multiple data points to determine capacitance. This provides a level of noise immunity, which is particularly important for sensing applications in variable environments. Another advantage is that the method does not have any specific requirements for a particular voltage waveform. As long as the sensing voltage causes a perturbation of the DE’s current and charge, a unique plane (and therefore capacitance) can be determined in 3D space. This allows simple digital PWM channels on portable microcontrollers and field-programmable gate arrays (FPGA) to be used as the excitation source, a key enabler for measuring large numbers of sensors on the body.

Unfortunately these benefits come at the cost of slower feedback as the plane-fitting process is computationally intensive. A typical self-sensing unit based on this method was reported to have a feedback rate of 10 Hz [59]. This becomes a trade-off for large numbers of sensors as high end processors are generally more expensive and power hungry.

An alternative method to determine capacitance is to model the DE’s impedance frequency response [49], [69], [86], [110], [118], [135]. As the impedance of the capacitive element in the DE ($X_c$) is frequency dependent (Equation 2-17), it disappears from the DE model at low frequencies as the
impedance approaches infinity ($X_c \to \infty$). Conversely, at high frequencies it approaches zero ($X_c \to 0$), which short circuits the parallel resistance. These simplifications are shown in Figure 2-20.

$$X_c = \frac{1}{j\omega C}$$  \hspace{1cm} 2-17

(a) At low frequencies  \hspace{1cm}  (b) At high frequencies

![Circuit Diagram](image)

Figure 2-20: (a) At low frequencies, the impedance of the capacitor approaches infinity, which causes it to drop out of the lumped parameter model. (b) Similarly at high frequencies, the impedance approaches zero, reducing the DE model to only its series electrode resistance ($R_s$).

Using these simplifications, Haus et al. [69] noted that the DE’s capacitance can be determined by performing an impedance sweep and extracting the characteristic features from Figure 2-21.

![Impedance Graph](image)

Figure 2-21: All three DE parameters can be deduced by performing an impedance frequency sweep on the DE and extracting features from the low frequency, high frequency and 3dB cut-off frequency response. (Adapted from [69])

The disadvantage of this technique is that performing multiple frequency measurements may be too slow for real time feedback. In addition, the extraction of features require further computational resources, and thus reduces the scalability of this approach for larger sensor networks.
2.3.4. Transmission line model

The previous three DE models all assumed a lumped parameter representation. Whether this is a single capacitor or a capacitor coupled with a series and parallel resistor, the electrical behaviour of the DE is assumed to be identical to its circuit model.

Although these models are generally sufficient to explain most DE behaviours, when do they start to break down? At what point do the distributed properties start to become significant? Could this be exacerbated by a high electrode resistance? Researchers trying to answer these questions have modelled the DE with a distributed electrical transmission line [55], [86], [133], [134], [137], [138]. The basic premise is to break the DE into an infinite chain of smaller, distributed capacitors and resistors as shown in Figure 2-22. Kaal et al. [134] noted that, provided that the DE is significantly longer than its width, the lateral effects can be neglected.

![Figure 2-22: The RC transmission line model assumes the DE is comprised of a distributed chain of smaller capacitors and resistors.](image)

There are many variations of this model, each containing or omitting certain elements depending on the DE materials used. For instance, Jung et al. [133] omitted the in-plane sheet resistance of the electrode ($R_s$) and added a thickness resistance instead. This variation was also used by Prof. Schlaak’s research group in their stacked DE models [69], [106], [110], [118]. Matysek et al. [138] showed that if the interconnecting resistances within the stack layers are low, the transmission line can be reduced back to the conventional DE lumped parameter model.

One important insight provided by the transmission line model is that the voltage is not uniform throughout the electrode [134], [137]. Graf and Maas [137] showed that the magnitude of the voltage reduces with increased distance from the connection point and that this effect is more severe at higher
frequencies. However, no discussion of how this affects the performance of the DE as a sensor was given.

O’Brien et al. [55] noted that if the sheet resistance of the electrode is too high, the DE may no longer adhere to the lumped parameter model, leading to errors. While the suggestion for preventing this was to reduce the frequency of the sensing signal, no quantitative analysis was provided.

In summary, while there has been analysis of the voltage distribution of the DE transmission line, no discussion of its potential for localised sensing exist. This is particularly true for possible methods to sense the individual capacitors in the transmission line, a feature which could significantly improve the scalability of DE sensing systems.

2.4. Contributions of this thesis

The literature review revealed a great deal of potential for DEs as wearable motion sensors. However three core challenges were identified which limit their adaptation for large scale implementation such as in a sensing suit.

1. Lack of efficient, robust, low voltage sensing methods

Most of the robust capacitance sensing methods that can accommodate DEs with non-ideal electrodes have been derived from self-sensing principles. These typically involve the use of large bulky electronic components that operate at high voltages, a factor that can compromise the safety of the user. Additionally, most techniques were demonstrated in laboratory settings and lack the energy efficiency required for long term outdoor monitoring. The sensing algorithms are also relatively complex, especially in the case of the Hyper-plane method which involves multiple computational steps. This increases the software overheads on portable microprocessors whose computing power should be reserved for higher level functions.

Chapter 3 addresses this problem by implementing a low voltage, multi-channel sensing architecture. It also introduces a new charge tracking method that is highly efficient and uses a DC voltage as the sensing signal. This eliminates unnecessary switching losses from discharging the DE. The method can also be implemented entirely in hardware to further reduce the required computational resources. These improvements help to simplify capacitance sensing methods so that they can be more efficiently used in a DE system.

2. Lack of guidelines for designing a sensing frequency

Most of the methods discussed such as the gain and phase and the current integration techniques require the choice of a sensing frequency. Since the capacitance of DEs are typically lower than
conventional capacitors, we need the flexibility to select a particular frequency so that we can optimize the system's sensitivity. Unfortunately, as a consequence of the use of low cost carbon materials in electrodes, large DEs are vulnerable to errors if the sensing frequency is too high. However, there is a lack of quantitative analysis on how this can affect the measurement of capacitance.

Chapter 4 discusses the importance of sensing frequency selection and why incorrect choices might lead to the underestimation of the DE’s true capacitance. It then provides a design guide to assist with the selection of an appropriate sensing frequency for a given DE design.

3. Limited scalability to a large number of sensors

Finally, no existing method has the ability to localise the deformation within a single DE or to discretize it into multiple sensing elements. This is a key scalability limitation as current sensing systems require extensive wiring, connectors and sensing hardware to measure multiple degrees of freedom. Even though a distributed transmission line model has been proposed, no current capacitance sensing methods take advantage of this in order to detect local capacitance changes.

Chapter 5 introduces a new capacitance sensing technique that can localise pressure from within a single DE. This enables it to be sectioned into many independent sensors to cover different parts of the body. Chapter 6 takes this further by demonstrating how the capacitance sensing principle could be applied in two dimensions in order to map strain. An efficient algorithm which allows each segment’s capacitance to be calculated simultaneously will also be presented.
Low voltage architecture

Publications

The contents of this chapter were published in:

1. The conference paper “Scalable sensing electronics towards a motion capture suit” in Proceedings of SPIE 8687, Electroactive Polymer Actuators and Devices (EAPAD) [139].
2. The conference paper “Enabling large scale capacitive sensing for dielectric elastomers” in Proceedings of SPIE 9056, Electroactive Polymer Actuators and Devices (EAPAD) [132].
3. The international PCT patent “Pliable capacitive structure apparatus and methods” [140].

As we saw in Chapter 2, there is a huge potential for the use of DEs in the field of motion capture. Whether our aim is to examine our technique during sports coaching, or to detect hand gestures for controlling computer interfaces, DEs can be used in a variety of applications to improve and enhance our lives.

However, not all DEs are equal as there is a large variation in the quality of the materials used to make them. Low cost DEs are usually made from carbon-based electrodes that have a high, strain-dependent resistance. This creates problems for the conventional capacitance sensing methods, which were not designed to handle capacitors with non-ideal properties. Unfortunately, the methods that do work were developed for self-sensing applications. They typically operate at high voltages, use bulky laboratory equipment and require extensive post processing for the calculation of capacitance.

This chapter creates a junction between these two approaches. First, we present a low voltage sensing architecture that can measure multiple non-ideal DEs. It achieves this by multiplexing the sensing signal and adapting the robust methods used in self-sensing to low voltages. Second, to improve efficiency, we present a new charge tracking method that uses a DC sensing voltage. This is more efficient as it does not incur any unnecessary switching losses during the sensing process. The method also performs the capacitance calculations locally in hardware to relax sampling requirements,
thereby enabling the use of low-end microprocessors. These improvements help to simplify DE sensing systems so that they can be more efficiently used to measure human body motion.

### 3.1. Soft game controller

One motion controller that requires a high degree of robustness is the arcade joystick. Over the course of its lifetime, it is likely to be the subject of physical abuse from adolescent boys. To increase their lifespan, joystick controllers were traditionally made from rigid parts and mechanical sensors (Figure 3-1). Unfortunately, these hard components can cause hand injuries during long playing sessions [141], [142].

![Figure 3-1: A traditional joystick controller is comprised of nothing but rigid components, which increases the risk of gaming injuries.](image)

One solution is to replace these mechanical parts with components made from soft materials such as rubber. DE sensors are ideal for this role as their natural elasticity provides a form of shock absorption and tactile feedback. Additionally, since DEs are analogue sensors, they can provide more precision than traditional binary buttons. This rewards skilled players with better control than the erratic ‘button bash’ tactics that are responsible for many injuries.

To construct a joystick with DE sensors, a thin 100μm sheet of a silicone elastomer was cast and layered with four keys made from carbon-powdered electrodes. These were equally spaced in a circle and the entire sheet was clamped around an acrylic ring so that the sensing regions could be stretched (Figure 3-2a). This design offers three translational degrees of freedom in the X, Y and Z axes.

Since the joystick was modelled after the size of its mechanical counterpart, each DE sensor only had a capacitance of approximately 100pF. To double the device’s sensitivity, the sensors were configured in differential pairs (Figure 3-2b). For instance, moving the central hub to the left stretches sensor C₃, which increases its capacitance. At the same time, this relaxes sensor C₁, thereby decreasing its capacitance. Thus, combining the difference between the sensors produces twice the capacitance sensitivity compared to a model in which only one sensor is measured. By using two sensors to map
the X direction and another two for the Y direction, we were able to effectively decouple the in-plane motion. The click function was programmed to sense an increase in the capacitance of all the sensors caused by a downward motion. The next section will discuss the ways in which traditional DE self-sensing techniques were adapted to measure capacitance at low voltage.

![Figure 3-2: (a) A soft joystick controller comprised of DE sensors. Four sensing zones were used to measure motion in three axes. (b) Look up table for mapping capacitance changes to game controls.](image)

### 3.2. Low voltage multiplex design

Professional gamers pride themselves on their ability to achieve pin-point accuracy and control. To emulate this, the Hyper-plane capacitance method [81] was used to measure the DE’s capacitance. Unlike other methods, it performs an averaging technique to reduce noise and accounts for the non-ideal properties of low conductive electrodes. The trade-off is the high level of computation required to calculate the capacitance. Specifically, this requires finding the determinants of the matrices given
in Equation 3-1, where \( V \), \( I \) and \( Q \) represent the voltage, current and charge collected over a given period [139].

\[
C = \begin{bmatrix}
\sum QV & \sum VI & \sum VT & \sum V \\
\sum Qi & \sum i^2 & \sum iT & \sum i \\
\sum QT & \sum iT & \sum i^2T & \sum iT \\
\sum Q & \sum I & \sum T & \sum 1 \\
\sum V^2 & \sum VI & \sum VT & \sum V \\
\sum Vi & \sum i^2 & \sum iT & \sum i \\
\sum VT & \sum iT & \sum i^2T & \sum iT \\
\sum V & \sum I & \sum T & \sum 1
\end{bmatrix}
\]

Since it can be difficult to implement the required level of computation on low-end microprocessors, we applied a ‘design for requirements’ strategy. By recognising that typical human reaction speeds are around 10 - 100ms [143], we were able to slow down the sensing speed while still maintaining a responsive controller. This gave sufficient time to sequentially measure each sensor while still meeting the speed requirements. This technique was implemented using a multiplexer (MUX) to switch the sensing signal between each of the DEs sequentially. Using this approach, we were able to eliminate a considerable amount of redundant hardware when compared to a parallel approach (Figure 3-3).

**Figure 3-3:** By designing the system to match the reaction speed of typical gamers, we could simplify the system by multiplexing the sensing signal and sharing the sensing hardware.

Since the Hyper-plane method requires knowledge of the charge on the DE, we needed to integrate current. Although this could be performed in software, a hardware integrator was implemented to relax the high sample rate normally required for this operation. To provide further tolerance,
instrumentation amplifiers with adjustable gains were used to measure the voltage and current. This provided a system with a wide dynamic range from 10pF to 10,000pF.

The measurement of each sensor was synchronised with a data acquisition unit using a hardware counter. This ensured that the selected DE was measured at the right time. A total of eight channels were implemented in a design dubbed the **OCTOSENSOR** (Figure 3-4). To test its efficacy, a periodic displacement device was designed to stretch a sample sensor. The resulting displacement was measured simultaneously by a laser which showed a good correlation between capacitance and strain (Figure 3-5). A resolution of 1pF (20µm) was achieved.

![The OCTOSENSOR capacitive sensing circuit and specifications.](image)

**Figure 3-4: The OCTOSENSOR capacitive sensing circuit and specifications.**
Because of the DE’s relatively low capacitance, it was important to maximize the sensitivity of the capacitance sensing system. Since the impedance of the capacitive element in the DE is frequency dependent, we can adjust the frequency of the sensing signal to achieve a larger response.

To understand this phenomenon, consider a DE sensor that is stretched from a capacitance state of 1nF to 2nF as shown in Figure 3-6. At low frequencies, there is a low phase difference between the two states. This is even worse at high frequencies where both the phase and magnitude changes are small. Thus, operating near these regions can be problematic for low resolution hardware and is susceptible to noise. A good frequency choice produces a distinct change in both the magnitude and the phase response of the DE.
Figure 3-6: Frequency response of a DE sensor when stretched from a state of 1nF to 2nF. Good sensitivity can be achieved when there is a distinct change in both the magnitude and the phase response.

### 3.3. Capacitance hardware implementation

Multiplexing the sensing signal can be an efficient way to measure multiple DEs without compromising the response of video game controllers. This reduces both the size and the cost of the hardware. By relaxing timing constraints, we enabled the use of low-end microprocessors.

To further reduce computation, we can delegate the capacitance calculations entirely to hardware. This has two main benefits. First, we can reduce the sample rate by an order of magnitude as we no longer require the raw sensing signals to calculate capacitance. Second, it frees up the processor to perform higher level functions such as gesture recognition or control of computer interfaces. Figure 3-7 shows a gaming glove embedded with DE sensors to measure hand gestures for controlling a video game.

To implement a capacitance sensing algorithm in hardware, we required a method that was relatively simple so that a prototype could be constructed from basic circuit components. It was preferable that this should involve only arithmetic or logic functions.

Out of all of the methods discussed in Chapter 2, the Hyper-plane method [81] is the most computationally intensive since the plane fitting process requires the calculation of a series of 4x4 matrix coefficients. The gain and phase method [80] requires the generation of a sine wave and the calculation of its phase shift. The impedance method [69] requires the generation of multiple sine waves and a feature extraction process.
In contrast, the current integration method used by Matysek et al. [84] for self-sensing required only simple integration and division. It works by integrating current through the DE to determine its charge. The DE’s capacitance is calculated using Equation 3-2, where $V_c$ is the voltage on the capacitor (Figure 3-8). The difficulty is that $V_c$ cannot be measured directly as it is internal to the DE. To work around this, the method waits for approximately $3 \times RC$ time constants until the system becomes fully charged. In this state, $V_c$ is equal to the supply voltage ($V_s$), which is known. Then, by representing charge as the integral of the current, the DE’s capacitance can be determined using Equation 3-3.

\[
C = \frac{Q}{V_c}
\]
Once steady state is reached

\[ C = \frac{\int I \, dt}{V_s} \]

One benefit of this method is that the time constant (\( \tau \)) is usually in the order of micro to milliseconds, so the transient time can be ignored. However, one drawback is that it uses an alternating voltage signal. As discussed earlier, this creates unnecessary losses each time the DE is charged and discharged. A solution is to use a DC sensing signal and continuously keep track of the charge on the DE. Provided the sensing voltage remains constant, any changes in capacitance will be reflected in the movement of charge to or from the DE. Thus, we can use charge as a proxy for the DE’s capacitance (Figure 3-9).

![Figure 3-9: The area under each curve represents the charge on the DE for the normal and stretched states. If the sensing voltage is held constant, the difference in charge is directly proportional to the change in capacitance.](image)

To understand charge tracking in real time, consider the capacitance profiles from Figure 3-10, simulated with a fixed 1V input signal using the modelling tool LTSPICE. After an initial transient stage, the charge signal quickly matches the capacitance of the DE and tracks any subsequent changes. The simulation also shows the effect of the size of the electrode resistance, where a higher resistance causes a longer delay.

Unlike other methods that determine the DE’s electrode resistance to offset its capacitance calculation, the charge tracking method gets around this problem by waiting until a sufficient time has elapsed for its effect to be negligible. As long as sufficient time has elapsed for the system to reach a steady state, the electrode resistance no longer forms part of the equation. This is a simple and effective way to decouple the electrode resistance of the DE.
Figure 3-10: (a) Sample circuit for the demonstration of charge tracking. (b) Charge tracking profiles for two different series resistances. After an initial transient stage, the charge on the DE quickly reaches the same magnitude as the capacitance of the DE. As the DE is stretched and relaxed, the charge tracks these changes in capacitance.

To implement charge tracking from low cost, common circuit components, we used a low dropout voltage regulator (LDO) to maintain a fixed input voltage. A sensing resistor and voltage buffer were used to measure current, and this was integrated using a Deboo integrator to allow operation from a single supply voltage. A reset switch was added to handle any integration drift over time (Figure 3-11).

The output of the charge tracking circuit is an analog signal that is proportional to the capacitance of the DE. By stripping away unnecessary components and converting to a DC sensing signal, this method could be run continuously for over two weeks, powered by a single coin cell battery. The results are comparable in accuracy to those found using the Hyper-plane method which takes considerably longer to process (Figure 3-12).
By moving the capacitance sensing algorithm into hardware, we were able to acquire faster measurements. In addition, the charge tracking method freed up the processor to perform higher level functions such as gesture recognition. Examples of this application include providing visual feedback for hand motion and controls for playing video games (Figure 3-13). For the latter case, specific controls based on intuitive hand motion were used to play the game DOOM. For instance, firing a weapon coincides with the gesture of pulling the index finger. These gestures allow a more intuitive and fun way to interact with video games and computers.
Figure 3-13: Top: DE sensing glove to provide visual feedback for hand gestures. This can be used for controlling machines and non-verbal communication. Bottom: A hand gesture based video game controller for playing the video game DOOM.

3.4. Chapter summary

By enabling DE sensors to be measured efficiently at low voltage, we can incorporate them into wearable motion systems for applications such as gesture based communication and controlling video games. This chapter presented an efficient capacitance sensing architecture which uses a multiplexer to switch between different DE sensors. The Hyper-plane self-sensing algorithm was adapted for low voltage operation for this purpose.

A new capacitance sensing method called ‘charge tracking’ was also presented. This method is based on the current integration method developed for self-sensing, but uses a DC voltage to reduce switching losses. The method was entirely implemented in hardware in a small form factor, and can provide up to two weeks of continuous sensing from a coil cell battery.

It was also shown that the sensing frequency has a large effect on the sensitivity of capacitance sensing. Thus we need the flexibility to adjust the sensing frequency in order to ensure accurate results. In the next chapter, we will discuss additional considerations, particularly for larger DEs with highly distributed resistances, and present a design guide for selecting an appropriate sensing frequency.
Sensing frequency guide

Publications

The contents of this chapter were published in the paper “Sensing frequency design for capacitance feedback of dielectric elastomers” in Sensors Actuators A: Physical [144].

In the previous chapters, we learned that electrodes with poor conductivity can cause problems in capacitance sensing. While there are special methods that can take this into account, all of them are based on a lumped parameter assumption, i.e. that the DE consists of a single capacitive element. In Chapter 2, we saw that a more accurate representation is provided by splitting the DE into smaller constituents. This may be particularly true in the case of a sensing suit which may have many sensing regions with electrodes distributed over a large area.

Our suspicion as to whether this could cause an error in capacitance sensing was aroused when the same DE measured two different capacitance values at different frequencies (see Figure 4-1 and Figure 4-2). This was surprising because the DE’s capacitance (Equation 4-1) was not known to be frequency dependent, since its main parameters were based on geometric and material constants [145], [146].

\[ C = \varepsilon_r \varepsilon_0 \frac{A}{d} \]  

4-1
The DE was measured under exactly the same conditions, so why was there a difference in capacitance? What was the actual capacitance of the DE? These are important questions to answer if we are to use DE sensors to accurately measure our body motion. This chapter investigates the effect of sensing frequency on the capacitance measurement of large DE designs. We illustrate our results using two design configurations, the DE stack and roll, both of which have a large electrode area. By analysing their distributed electrical models, we will gain insight into why the capacitance
measurement could be affected by the frequency of the sensing signal. Finally, we will present a design guide on how to select an appropriate sensing frequency so that we can accurately measure capacitance.

4.1. Methods

To investigate the apparent capacitance discrepancy, we looked at two particularly large designs that have amplified distributed properties. These were the stacked and rolled DE configurations frequently used in robotic actuators and energy harvesters.

The DE stack, as its name suggests, is constructed by layering single, small DEs on top of each other to create a giant column structure. Its energy density (related to capacitance) is directly proportional to the number of layers in the stack. Two DE stacks were provided by the Swiss Federal Laboratories for Material Science and Technology (EMPA) for testing (Figure 4-3). These stacks consisted of alternating layers of a circular shaped electrode made from conductive Ketjenblack EC-600 carbon power, embedded in an IPN-modified VHB-4910 dielectric [117]. In order to increase the stack’s total capacitance, the layers were joined in parallel using conductive carbon grease. The two stacks contained a total of 1687 and 1344 individual DEs, respectively.

Unlike the multi-layered stacks, the DE rolls consisted of only a single sheet wrapped around a compressed spring to provide mechanical rigidity. The benefit of this design was its single large electrode which required no bridging connections. Metal pins were pierced through both ends of the roll to connect to the electrodes and serve as the feeding lines for the sensing signal. A total of four different rolls were tested (Figure 4-4).
We used the OCTOSENSOR sensing unit designed in the previous chapter to record the capacitance of the DE stacks and rolls. A LabVIEW interface was programmed to apply different capacitance algorithms for the calculation of the DE’s capacitance (Figure 4-5). These were the Hyper-plane [81] and current integration methods [84] discussed in the previous chapter. Both methods were designed specifically to handle large electrode resistances. Different sensing frequencies were tested.

All measurements were conducted under a low potential of 5 volts, which ensured negligible electroactive actuation and leakage current [69]. Since no physical stimulus was applied, any capacitance variation was entirely due to an electrical phenomenon and not the result of a mechanical deformation.

### 4.2. Results

The frequency sweep of the Hyper-plane and current integration methods showed a general capacitance decrease with frequency (Figure 4-6 and Figure 4-7, respectively). DE stack 1 showed a consistent capacitance drop with increasing frequency for both sensing methods. Stack 2’s capacitance was maintained at a relatively stable level until it succumbed to a similar effect at a
frequency of 1 Hz. No capacitance measurements were made at frequencies below 0.1 Hz due to a poor signal to noise ratio. The DE rolls exhibited a similar frequency response, but maintained a stable capacitance for a longer period before dropping with frequency. The results for the rolls are given in Figure 4-8 and Figure 4-9.

Even though both sensing methods were designed specifically to handle high resistance electrodes, the results showed that the capacitance measurement could be strongly influenced by the choice of sensing frequency. While the DE’s capacitance seemed to be constant at lower frequencies, higher frequencies resulted in a significant decrease in capacitance. To the author’s knowledge, this type of failure has not previously been reported. We now consider the causes of this dependence of capacitance on frequency, beginning with the current integration method.

**Figure 4-6**: Stack 1 and 2's capacitance frequency sweep with the Hyper-plane algorithm. Both the stacks' capacitances seemed to decrease with frequency.

**Figure 4-7**: A similar decrease was observed with the current integration algorithm.
Figure 4-8: Capacitance of four DE rolls measured using the Hyper-plane method.

Figure 4-9: Similar behaviour occurred with the current integration method.

4.3. Charged with integration failure

To understand why capacitance decreased at high frequencies, we began by examining any violations of the sensing assumptions. Recall that the current integration method works by calculating the net charge transferred to the DE from a known voltage. For a square wave sensing signal, it assumes that sufficient time has passed for the capacitor to become fully charged. In this state, the DE’s capacitance can be determined using the equation $Q = CV$ (Equation 4-2) and integrating current (Equation 4-3).

$$C = \frac{Q}{V_c}$$  

4-2
\[ C = \frac{\int I \, dt}{V_s} \]

To see how this can fail, consider Figure 4-10 which shows a 1 kHz square wave sensing signal. After the initial transient, the voltage on the capacitor \( (V_c) \) quickly matches the known supply voltage \( (V_s) \). This shows that sufficient time has elapsed for the system to reach its steady state. This is shown in Figure 4-11 where the current reaches zero at half of the period. At this time, 4-3 can be used to correctly calculate capacitance. An inverted response can be observed for the discharge cycle.

![Figure 4-10](image1.png)

*Figure 4-10: With a 1 kHz square wave sensing signal, the capacitor voltage \( (V_c) \) has adequate time to reach the supply voltage, allowing \( V_s \) to be used in the calculation of capacitance.*

![Figure 4-11](image2.png)

*Figure 4-11: The corresponding current response. Current exponentially decreases to zero as the system becomes fully charged. This signals that the total capacity of the DE has been sensed.*

However, when the sensing frequency was increased to 5 kHz, the steady state for the system was no longer attained. This can be seen from the voltage drop between \( V_s \) and \( V_c \) (Figure 4-12) and the charge deficit in the current cycle in Figure 4-13.
Figure 4.12: A 5 kHz sensing waveform with the period now significantly reduced. The voltage drop caused by the electrodes can now clearly be observed. This shows that the system has not reached steady state.

Figure 4.13: At 5 kHz, only a partial amount of charge was transferred to the DE. Hence the current integration method will under represent the capacitance of the DE.

The violation of the steady state assumption at high sensing frequencies explains the lower capacitance measurement for the current integration method. However, the Hyper-plane results also showed a capacitance decrease. Unlike current integration, the Hyper-plane method does not depend on the total charge, but calculates the capacitance from the intrinsic relationship between voltage, current and charge [81]. Its failure leads us to question a different cause for the offense.

4.4. Distributed model

To understand why the Hyper-plane method failed, we investigated three different electrical models of DE stacks: the ideal stack, a stack with high electrode resistance, and a stack with both high electrode and interconnect resistance.

An ideal stack is simply a parallel network of capacitors (Figure 4.14a). This is electrically equivalent to a single large capacitor whose capacitance is proportional to the number of units in the chain. However, a stack with carbon-based electrodes should also include a resistive term ($R_i$) to model the high resistance of the electrodes (Figure 4.14b). In a similar way to the ideal stack, this can be simplified to a lumped $RC$ equivalent circuit. Finally, our actual DE stack requires yet another resistive
term, the interconnect resistance \( R_c \) to represent the carbon grease binding the layers together (Figure 4-14c). Since this feeding line only connects at a single contact point, the sensing signal has to propagate sequentially through each segment of the chain before reaching the next capacitor. Unfortunately, this model can no longer be reduced to a lumped parameter equivalent.

![Diagram of ideal, high electrode resistance, and actual stacks](image)

Figure 4-14: (a) The ideal stack is simply a network of parallel capacitors. (b) A stack with a high electrode resistance \( R_s \). (c) The actual stack contains both electrode resistance and interconnect resistance terms \( R_c \). This model has no lumped parameter equivalent.

To quantify the effect of the interconnect resistance \( R_c \) on the capacitance measurement, we modelled one of the stacks using a distributed model consisting of 1433 segments, one for each DE layer. Each segment was approximated by a 170pF capacitor in series with a 6kΩ resistor [144], values which were calculated from the geometric and material properties of the segment (Figure 4-15). The interconnect resistance was estimated to be 600Ω/segment, based on an end-to-end measurement across the length of the stack.
Using this distributed model, we numerically calculated the electrical impedance for different values of \( R_c \) (0 Ω, 6 Ω, 60 Ω, 600 Ω and 6000 Ω). The condition \( R_c = 0 \) was also included to model a perfectly conductive chain. This resembles the model in Figure 4-14b which can be reduced to a lumped parameter equivalent. Figure 4-16 shows the magnitude of the impedance, plotted using MATLAB across a frequency range of 0.01 – 100,000 Hz.

In this plot, we see an initial overlap between the curves at low frequencies. However, as the sensing frequency was increased, the higher interconnect resistance caused a departure from the lumped parameter scenario. This also occurred earlier on the frequency axis for higher values of \( R_c \). This result shows that, while the effect of the interconnect resistance could be ignored at low frequencies, it had a significant effect on the stack’s electrical properties at high frequencies.

We then calculated the current response and applied the Hyper-plane algorithm in a simulation to determine how this difference affected the stack’s measured capacitance. We can see from the results in Figure 4-17 that the capacitance was initially constant, but then decreased with frequency, just like the measured results. This initial capacitance at low frequency was equal to the nominal value for the
As the frequency increased, the capacitance progressively tapered off. This occurred at lower frequencies for higher values of the interconnect resistance. (The small capacitance offset between the measured results and the nominal capacitance was most likely due to incomplete connections to all of the layers in the actual stack).

![Figure 4-17: Capacitance frequency simulation of the distributed transmission line model for different interconnect resistances.](image)

From these simulations, it is apparent that the drop off in the capacitance measurement at high frequencies is due to the interconnect resistance between the layers. However, this does not mean that the actual capacitance of the DE has changed.

The cause is due to a breakdown of the lumped parameter assumption as the DE starts to behave like a transmission line with higher frequencies. At low frequencies, this is negligible, but it becomes progressively more significant at higher frequencies. The next section will show how we can quantify this error.

### 4.5. Coercion

The underlying assumption in both the Hyper-plane and current integration sensing methods is that the DE adheres to a lumped parameter model. Thus, when this model was no longer valid, as was the case for the large DE stacks and rolls, both methods suffered a coercion error which arose from force fitting the solution. To quantify this, we will first derive the complex impedance of the lumped parameter model and then compare it with the distributed impedance of the stack.

Most DE capacitive sensing methods use the lumped $RC$ model shown in Figure 4-18. This model's electrical impedance consists of a real and an imaginary component that independently represent the resistive and capacitive elements of the DE (Equation 4-4).
59

\[ Z_{\text{total}} = R_s - \left( \frac{1}{\omega C} \right) j \]  

4-4

To see what happens when a distributed model is coerced under this assumption, we consider the simple two segment example shown in Figure 4-19. Here, the electrical impedance is as given in Equation 4-5. This can be rearranged to form Equation 4-6, which has the same format as Equation 4-4. Now, if we compare the real and imaginary components of these equations, we see that the resistance and capacitance terms are no longer independent for the distributed model, but have become intertwined.

\[ Z_{\text{total}} = 2R_c + \frac{(R_c + R_s) \left[ R_s (2R_c + R_s) + \left( \frac{1}{\omega C} \right)^2 \right]}{2 \left[ (R_c + R_s) + \left( \frac{1}{\omega C} \right)^2 \right]^2} - \left( \frac{1}{\omega C} \right) \left[ R_c^2 + (R_c + R_s)^2 + \left( \frac{1}{\omega C} \right)^2 \right] j \]  

4-5

4-6

An interesting simplification of the distributed model’s impedance occurs when the interconnect resistance is negligible \((R_c = 0)\). It is then reduced to the lumped parameter model shown by Equation 4-4.
4-7. This was the case for the DE stacks used by Haus et al. [69] which used metallic feeding lines rather than carbon grease to bridge the layers.

\[
Z_{\text{total}} = \frac{R_z}{2} - \left( \frac{1}{2\omega C} \right) j
\]

Finally, we illustrate the capacitance frequency coercion with an example. Although the circuit on the left in Figure 4-20 has two 100nF capacitors in parallel (total capacitance = 200nF), if we apply a lumped parameter capacitance sensing method, we will measure a different capacitance value. This highlights the fact that while we may be able to get away with using the wrong model at low frequencies, we will be increasingly misled at higher frequencies.

![Figure 4-20: The capacitance of a two segment distributed model and its coercion under a lumped parameter assumption. All of these circuits have the same electrical impedance.](image)

### 4.6. How we roll

The previous section identified that the capacitance frequency dependency was due to the departure from a lumped parameter model. While an analytical quantification of this effect could be derived by determining the DE’s complex impedance, a practical test can be used to quickly see if the lumped parameter condition is met. We will use the DE roll configuration to demonstrate this technique.

When uncoiled, the roll resembles a large planar DE (Figure 4-21). One characteristic of this design is its rather large aspect ratio which can be tens to hundreds of times larger than the individual stack layers. It can be modelled by a 3D network of discrete resistors and capacitors, similar to the distributed model for the stack.
Figure 4-21: The rolled configuration resembles a planar DE with a large aspect ratio. The extreme length amplifies the distributed effects of its high resistance electrodes.

The consequence of this distributed network is the increased distance that the sensing signal has to travel to reach different parts of the electrode. For a small length, this may be insignificant, but in a large sensor, the attenuation from the electrodes may cause large differences in voltage at different parts of the electrode. To see this, consider Figure 4-22, a simplified version of the model with the lateral effects ignored. At a 1 Hz sensing signal, the voltage is uniform throughout all parts of the electrode. However at 10 Hz, the far edges of the electrode start to show a reduction in the sensing signal. This becomes more pronounced when the frequency is further increased to 100 Hz. Thus, by measuring the voltage on different parts of the electrode, we can determine whether the sensing frequency satisfies the lumped parameter assumption.
4.7. Choosing a sensing frequency

A sufficiently low sensing frequency is important to accurately measure the capacitance of large DEs with distributed electrodes. To determine an adequate value, a number of mechanical and electrical properties need to be considered. First, we need to ensure that the sensing signal and the sample rate are fast enough to capture the mechanical deformation without aliasing, an effect where different signals become indistinguishable due to under sampling. The Nyquist-Shannon sampling theorem states that we need to sample at a rate of at least twice the frequency of the signal of interest. As a general rule of thumb, a 10x sample rate is recommended to reconstruct a signal with sufficient resolution.

Once a frequency has been determined which adequately captures the mechanical motion, it should be tested to ensure that it doesn’t violate the lumped parameter assumption used in the capacitance sensing. This can be evaluated by modelling the DE with a distributed model, computing its complex impedance and evaluating the lumped capacitance using Equation 4-8, or by testing the uniformity of the sensing voltage at various locations on the electrode. Alternatively, a manual capacitance sweep can be performed to determine the frequency at which the DE’s capacitance starts to roll off [Figure 4-23(b)].
While a high sensing frequency is beneficial for improving the rate of capacitance feedback, care needs to be taken to ensure that the use of this frequency does not violate the lumped parameter assumptions of the sensing methods. It is recommended that the sensing frequency is set as high as possible, while still satisfying these accuracy requirements.

\[
C_{\text{lumped}} = -\left(\frac{1}{2\pi f \times \text{imag}(Z)}\right)
\]

Equation 4-8

Figure 4-23: (a) The mechanical response needs to be sampled with a fast enough sensing signal to prevent aliasing. (b) Once a minimum sensing frequency satisfying the Nyquist sampling criteria has been determined, it should be tested against the capacitance frequency response to ensure that it does not violate the lumped parameter sensing assumption.

4.8. Chapter summary

This chapter showed that the sensing frequency is an important consideration in ensuring the accuracy of capacitance measurements. This is especially the case for large DE designs with a highly distributed electrode such as in a sensing suit for measuring our body motion. If the sensing frequency is too high, the lumped parameter assumption used in the capacitance sensing algorithms can be violated. The result is an underestimation of the DE’s capacitance. While this is not ideal for measuring the total capacitance of the DE, we will show in the next chapter how we can exploit this phenomenon to measure local regions inside the DE, a key enabler for more scalable sensing systems.
Localised capacitance sensing

Publications

The contents of this chapter were published in:

1. The journal paper “Where the rubber meets the hand: unlocking the sensing potential of dielectric elastomers” in the Journal of Polymer Science, Polymer Physics [148].
2. The conference paper “Localised strain sensing of dielectric elastomers in a stretchable soft-touch musical keyboard” in Proceedings of SPIE 9430, Electroactive Polymer Actuators and Devices (EAPAD) [149].
3. The provisional patent “Capacitive Sensor” [150].

Soft sensors offer a high degree of compatibility with the human body. Whether for sports coaching, monitoring posture, or controlling videogames, they can provide valuable insights into how we move. One of the most active and sensitive parts of the body is our hands. From feeling our way in the dark to greeting friends, or typing on the computer, our hands are one of the main ways we interact with the world. Today, many computers and mobile devices have taken note of this by adopting touch and type control interfaces. Unfortunately, unlike our bodies, most of them lack any degree of flexibility and are thus susceptible to damage. Adding flexibility would not only give these devices a level of tolerance to damage but would also help to conserve space.

Imagine a full size keyboard that could fit into your pocket and be stretched out whenever needed. This is the potential that DEs can bring to soft interface devices. However, such a keyboard requires many keys or sensor channels. While all of the existing DE capacitance sensing methods can handle a few channels, scaling up is a challenge. This is because these methods are all fundamentally based on a lumped parameter model (Figure 5-1), where each DE is assumed to be a single capacitor. Thus
adding new keys requires additional wires, connectors and electronics which rob the DE of its intrinsic softness and flexibility.

In order to increase the sensing potential of DEs for applications such as soft keyboards, we need to address this fundamental scalability challenge. In this chapter, we present a new sensing method that is capable of differentiating localised capacitance changes and thus allows the DE to be discretized into multiple regions. Not only does this reduce the amount of wires and sensing electronics, it also simplifies the fabrication process since making a single large sensor is much easier than making multiple smaller sensors. To achieve this, we will build on the results of the previous chapter by adopting the continuous transmission line model.

5.1. The transmission line model

To use DEs more effectively, we need to break away from the lumped parameter capacitor model. As with any capacitor, its behaviour adopts a distributed effect when there is a significant electrode resistance [151]. In other words, rather than conforming to a single capacitor, the resistance separates the DE to a composition of smaller capacitors. As discussed in Chapter 2, the transmission line model [55], [134], [137], [152] has been proposed for typical DEs in which the electrode resistance can be up to 100s of kΩs [67].

At this granular level, they are represented by chains of smaller capacitors and resistors in a ladder network. A single unit of this chain is shown in Figure 5-2. This allows different sections of the DE to be represented by their own local capacitances. Using the transmission line model, we can analyse the internal changes in these capacitors and thus determine the location of a key press on different parts of the DE (see Figure 5-3).
In the transmission line model, the sensing voltage as a function of distance \( z \), can be derived by solving a pair of Telegrapher’s Equations 5-1 & 5-2. For a relatively short length and high dielectric insulation, we can ignore the inductance \( (L') \) and conductance \( (G') \) terms of the model.

\[
\frac{\partial V}{\partial z} = -L' \frac{\partial I}{\partial t} - R'I \tag{5-1}
\]

\[
\frac{\partial I}{\partial z} = -C' \frac{\partial V}{\partial t} - G'V \tag{5-2}
\]

The solution of this pair of differential equations can be found analytically using Laplace transforms [137]. The general form of the voltage solution resembles Equation 5-3, where \( \omega \) is the angular frequency of the input voltage, \( \zeta \) is the wave propagation constant Equation 5-4, and \( V^+ \) and \( V^- \) are
the magnitudes of the voltage waves travelling forwards and backwards along the transmission line, respectively.

\[ V(z, t) = V^+ e^{(j\omega t - \zeta z)} + V^- e^{(j\omega t + \zeta z)} \]  

To illustrate how this voltage changes along the length of the transmission line, we used MATLAB to simulate input signals of different frequencies for a DE of length 0.1m with a homogeneous resistance and capacitance profile of:

\[ R' = 1\, \text{M} \Omega / \text{m} \]
\[ C' = 1\, \text{nF} / \text{m} \]

In Figure 5-4(a), where the sensing frequency is 100Hz, we see that the internal voltage is uniform throughout the entire distance of the DE. This means that every part of the sensor experiences the same voltage at instant in time. However, this is not the case with a sensing frequency of 10kHz [Figure 5-4(b)], as the voltage decreases significantly with increased distance from the origin. This effect can be reversed by reducing the resistance of the electrodes from 1M\( \Omega \)/m down to 10k\( \Omega \)/m as shown in Figure 5-4(c).

These visualisations provide two important insights about the DE transmission line model. First, we note that the resistance of the electrodes (\( R' \)) has a strong influence on the reach of the sensing signal. A low resistance allows the sensing voltage to travel further into the electrode, and thus to detect more of the capacitors in the chain. Second, the frequency of the sensing signal can be adjusted as a counter measure against the high resistance since lowering the frequency gives the voltage more time to propagate. Therefore, by adjusting the frequency of the sensing signal, we can alter how far along the transmission line we can selectively measure.
Figure 5-4: (a) At low sensing frequencies, the internal voltage is uniform along the length of the DE. (b) As the input frequency is increased, the voltage suffers attenuation. (c) This effect can be reversed by reducing the resistance of the electrodes.

5.2. Localised sensing principle

The transmission line simulation shows that the amplitude of the sensing voltage becomes smaller the further it travels into the electrode. A key notion is that, at some point, it will become insignificant in size and fail to measure the remaining capacitors in the chain. This can be controlled by the choice of sensing frequency as a lower frequency has a greater ‘reach’ than a higher frequency. This enables us to target a particular section of the DE using different sensing frequencies (Figure 5-5).

Figure 5-5: Lower sensing frequencies are sustained longer in the transmission line and are thereby able to measure a greater proportion of the total capacitance. By comparing the capacitance measured at different frequencies, we can thus determine local changes in capacitance.
This result can be extended by marking the length at which a sensing frequency loses its ability to detect changes in capacitance and comparing this with the corresponding length for a different frequency. The difference between these two measurements represents the local capacitance within a section of the DE (Figure 5-6).

![Diagram of local capacitance and lumped model](image)

**Figure 5-6:** The lumped capacitance difference at two different frequencies indicates the number of capacitors between these two sections.

To test this theory, we constructed a DE sensor from a 100μm thick PDMS dielectric film sandwiched between two carbon-based electrodes. The resulting sheet was cut into an area of approximately 0.1m x 0.14m and metallic terminals were connected to one end of the electrodes to create a transmission line. The total capacitance and electrode resistance of the DE were approximately 220pF and 250kΩ, respectively, values which were measured at a low sensing frequency. The sensor was divided into four regions which corresponded to different keys for the control of a musical keyboard (Figure 5-7).

To identify the sensing frequencies corresponding to each section, a frequency sweep of the DE’s capacitance was performed from 100Hz to 100 kHz. The results showed a consistent measurement at low frequencies, representing 100% of the capacitors in the transmission line. However, beyond a sensing frequency of 1 kHz, the measured capacitance started to decrease (Figure 5-8). As discussed in the previous chapter, this was caused by coercion of the DE to fit the lumped parameter model required for the sensing method.
It is important to note that these tests were conducted at a low voltage (1V) with no physical deformation applied to the DE. In addition, the dielectric constant of the PDMS elastomer specified a constant value across the frequency range of the tests. Thus the measured capacitance decrease was not due to an actual change in the DE’s geometry, but rather an artefact of the lumped capacitance model.

Based on these capacitance measurements, four sensing frequencies (1 kHz, 8 kHz, 14 kHz and 30 kHz) were selected to represent the four different regions on the DE keyboard (Figure 5-9). These corresponded to approximately 25% increments in the measured capacitance. For example, the highest frequency signal (30 kHz) was used to detect changes in the first 25% of the sensor’s length, and the next frequency (14 kHz) up to 50% of the sensor’s length.
To use the DE sensor as a controller for a musical keyboard, the frequency signals were first summed together in LabVIEW and sent to a current driver via the data acquisition card (NI USB 6351). After measuring the current response, a band-pass filter decomposed the signal, searching only for the targeted frequency components. The decomposed signals were then used to calculate the capacitance at each frequency in order to determine which region of the sensor was pressed. A sound corresponding to the selected key was then played through a loudspeaker. Figure 5-10 illustrates this process.
Figure 5-10: Four sensing frequencies were combined and simultaneously sent to the DE keyboard. A band pass filter was used to decompose these frequency components for calculation of the corresponding capacitance. Finally, a matching algorithm was used to compare against a threshold value to determine which note to play via the loudspeaker.

5.3. Results

As the transmission line model had predicted, the sensing frequency could be used to differentiate which key was pressed. Figure 5-11(a) shows that at a sensing frequency of 1 kHz, all four key positions produced an identical capacitance change since the frequency was low enough for all regions to experience the same sensing signal. However, at higher frequencies, pressing on different keys resulted in different capacitance changes. For example at 8 kHz, pressing key number 1 (closest to the origin) registered a 16pF change, which was twice the capacitance change for key number 4 (furthest away). Comparing these differences allowed us to determine which key was pressed at any given time.
Figure 5-11: Capacitance frequency response of single and multiple presses. We used the high frequency components to determine which key was pressed, and the low frequency component to determine how many were pressed.

This method could also determine how many keys were pressed simultaneously. Consider the low frequency response of Figure 5-11(b). Below a frequency of 1 kHz, the sensing signal was slow enough to travel to all parts of the sensor. Thus, pressing one key resulted in an approximate 22pF change in the total capacitance, while pressing two keys at once doubled this amount. Hence, by comparing the capacitance change of the sensor at different frequencies, we could identify which key (and how many keys) was pressed (Figure 5-12).
Figure 5-12: Pressing locations further down the transmission line shows a lower change in capacitance. A simple threshold could be used to identify which key was pressed. Note, only a single pair of wires were used to sense the four different regions.

5.4. Discussion

The motivation for using the transmission line approach was to reduce the number of wires, connectors and sensing electronics required for large sensing systems such as in a sensing suit. We found that the sensing frequency is a tuneable property that can be used to discretize a single DE into multiple regions. This dramatically improves the scalability of DE sensing systems.

One assumption of the model was that the DE was homogenous with a constant capacitance and resistance profile. However, this was difficult to control in the fabrication process, resulting in some cross-over between some of the frequency components. One solution to this problem is to compare multiple frequencies at the same time and impose a threshold amount by which the capacitance has to change in order to definitively register as a press.

As already discussed, the resistance of the electrodes plays an important role in the DE’s frequency response. While previously viewed as an unfavourable characteristic, this property produces the voltage gradient that lies at the core of this sensing method. By using sufficiently high resistance
electrodes, we can shift the frequency bandwidth to lower frequencies, reducing the need to sample at high speeds (Figure 5-13).

![Figure 5-13: The capacitance frequency profile can be lowered by using higher resistance electrodes, pushing the curve to the left.](image)

For any human body sensing application, eliminating electrical noise from stray capacitances can be a difficult problem. The human body itself can possess a large capacitance of up to 400pF, depending on footwear and floor insulation [153]. This can introduce an error in the capacitance reading of the sensor. One mitigation strategy is to increase the total capacitance of the DE by using more layers (in the form of a small stack). Another safeguard is to include a pair of shielding electrodes on the outer layers which help to protect the sensor from this noise (Figure 5-14).

![Figure 5-14: Additional ground electrode layers can be added to shield the sensor from environmental noise.](image)

5.5. Chapter summary

This chapter has significantly increased the utility of DE sensors. It has shown how we can discretize a single sensor into multiple regions without adding any new wires, connectors or sensing electronics. We have presented a new sensing method that is able to determine the location of local capacitance changes within the DE. By modelling the DE as a continuous transmission line, we have seen that the once unfavourable characteristic of high resistance electrodes can be used to manipulate the efficacy of different frequency sensing signals. By applying multiple sensing frequencies simultaneously to the DE, we were able to determine which section of the DE was pressed. This approach simplifies large sensing systems as we no longer require individual sensors for each degree of freedom. In the next chapter, we will show how this concept can be extended into two dimensions for strain mapping.
Two dimensional sensing

Publications

The contents of this chapter were published in:

1. The journal paper “Stretch not flex: Programmable rubber keyboard” in *Smart Materials and Structures* [154].
2. The international PCT patent “External Coupling Sensor” [155].

Do you remember the feeling of walking off track and getting lost? How about the relief that you felt as soon as you found your old footprints? Information is all around us, sometimes right under our feet. One application of DE sensors is to map foot pressure distribution. Imagine a smart shoe that could tell you when you were walking incorrectly and at risk of injury. To construct such a device, we first need to be able to measure pressure in two dimensions.

In the previous chapter, we demonstrated the ability to measure local capacitance changes inside the DE. This allows a single sensor to cover different areas of the body and effectively function as if it were multiple sensors. Not only does this increase the efficiency and ease of manufacture, it also significantly reduces the number of wires, connectors and sensing electronics required for a sensing suit. This chapter takes the concept of localised capacitance sensing further, extending the principle into two dimensions. By adding a second sensing dimension, we can dramatically increase the number of sensing regions over a given area. This will greatly enhance the utility of DE sensors (Figure 6-1).

In order to sense a large number of locations efficiently, a multi-frequency sensing technique is required. This chapter presents such a technique, based on a *Fast Fourier Transform (FFT)*. Our technique allows the capacitance of different regions of the DE to be measured simultaneously, thereby increasing the speed of the response. By controlling the sensing resolution in software, we
create the ad-hoc ability to measure different body parts without the need to change the sensor configuration.

Figure 6-1: A DE sheet can be made into a sensing skin to cover large areas of the body. By sensing local capacitance changes in the sheet, we can determine where the deformation is happening.

6.1. 2D method

Rather than using $n$ sensors to distinguish $n$ positions, we demonstrate how to discretize and localise internal capacitance changes in two dimensions without the need for a large number of wires (Figure 6-2). Our technique is based on the distributed transmission line model presented in the previous chapter which uses different sensing frequencies to separate the DE sheet into smaller constituents.
In the transmission line method, high resistance carbon-based electrodes are used to create a voltage gradient internally in the DE. This presents different levels of attenuation for different sensing frequencies. High frequencies are strongly affected and only appear to have a significant presence near the origin, whereas low frequencies maintain their strength for the entire length of the sensor. By combining a sensing signal with both low and high frequency components, we can differentiate local changes in capacitance (Figure 6-3).
Since the model is continuous, intermediate frequencies can also be added to the sensing signal to further increase the spatial resolution. Thus we can easily enhance our model without additional cost. By comparing the capacitance change between two adjacent frequencies, we can infer the pressure difference between their boundaries.

To enable the detection of pressure in two dimensions, we placed one DE layer on top of another and laminated them together. One of the two sensing layers was oriented along the X-direction while the other was oriented along the Y-direction. This allowed for the electrical isolation of the two sheets while their mechanical response was coupled.

The same sensing signal was simultaneously applied to both layers, using electrodes placed at a 90 degree angle, thereby forming transmission lines in each of the two directions (Figure 6-4). The electrodes were connected along an entire edge to create a uniform electric field in their propagating directions. These sheets were made from a PDMS dielectric of approximately 100µm in thickness, together with conductive carbon-based electrodes. A common middle electrode was used as the ground return for both DE sheets.

![Figure 6-4: The sheet was constructed with 5 layers of alternating electrode and PDMS dielectric. The electrodes were placed at a 90 degree angle to create two separate transmission lines in their respective directions.](image)

To measure the capacitance in both the X and Y directions, two separate capacitance sensing circuits were used to excite the sensor sheet. The **OCTOSENSOR** capacitance sensing system presented in Chapter 3 was reprogrammed for this purpose.

A capacitance frequency sweep was conducted to determine the frequencies required for sensing different regions of the DE. The results (Figure 6-5) showed a similar frequency response for both sensing layers. On the basis of these results, a low and high frequency component (1 kHz and 60 kHz, respectively) were combined to form the sensing signal. The low frequency component was used to measure the far regions of the sheet, while the high frequency component measured the parts of the sheet near the origin.
Figure 6-5: The frequency response for both sensing layers showed a similar decrease in capacitance with frequency due to transmission line attenuation.

6.2. Parallel capacitance calculations

An important requirement for sensing multiple regions is the ability to respond quickly to different key presses. One possibility is to sequentially measure one region at a time by sweeping through different sensing frequencies. However, not only is this slow, but the comparison of multiple frequencies is required to identify the positions and sizes of the key presses. This can lead to a time-lapse error if not all of the regions are compared at the same time. To overcome this problem, we implemented a multi-frequency capacitance sensing technique that could synchronise timing and increase speed.

Our solution first combined the selected frequencies into one common signal. This effectively excited the sensor with all of the frequency components at once. Next, a Fast Fourier Transform (FFT) was performed to extract the gain and phase shift of each frequency. As discussed in Chapter 2, these parameters are directly linked to the capacitance calculation algorithm [80], [85]. This method allowed
us to compare the capacitance of the sheet for a number of different frequencies at the same time, a process which is much faster than a sequential approach (Figure 6-6).

Figure 6-6: Sequentially sweeping through each sensing frequency can be slow and susceptible to time lapse errors. A solution is to measure all frequencies at the same time using a Fast Fourier Transform.

The sensing signal was digitally created in software to allow programmability for additional keys at a later stage. It was simultaneously applied to both sensing layers through a data acquisition card and current amplifier (Figure 6-7). The output current was captured using instrumentation amplifiers and filtered with 2nd order Butterworth low-pass filters to remove noise outside of the frequency range.
6.3. Results

The transmission line model showed that high frequencies are inadequate for measuring capacitors far away from the origin while low frequencies can measure capacitors anywhere in the sensor. This allows us to localise the position of the key press by comparing the high and low frequency capacitance. We can then use the low frequency capacitance to determine the overall displacement.

For testing, the sensor sheet was divided into four quadrants, and a series of four 5mm displacements were manually applied to each quadrant (Figure 6-8).
To determine the quadrant in which the displacement took place, we looked at the high frequency capacitance in both X and Y directions simultaneously. Due to the high resistance of the electrodes, pressing further away from the origin caused a smaller capacitance change than pressing closer by. This relationship provided a way to differentiate between each of the four quadrants in the sheet. For instance, as is shown in Figure 6-9, when key 1 was pressed, a large change in capacitance was registered in both the X and Y layers. However, when key 3 was pressed, the only significant change was registered in the X-layer since the high frequency signal in the Y-layer had suffered severe attenuation. A calibration was performed to determine the threshold level for a significant change.
6.4. Scaling up (3x3)

A benefit of this multi-frequency approach is that it can be easily scaled to further increase resolution when more keys are required. For instance, by adding an extra frequency component to the sensing signal, we can increase the sensing area from a 2x2 to a 3x3 array. To demonstrate this programmability, we used the same sensor as in the previous measurements and added an intermediate 20 kHz component to the sensing signal.

From the results displayed in Figure 6-10, we could determine the row in which the deformation occurred by comparing the Y-layer capacitance at all 3 frequencies. Since the low frequency component (1 kHz) reached all parts of the electrode equally, it measured the same capacitance change for all three rows. However, the effects of the electrode attenuation became apparent for the intermediate and high frequencies (20 kHz and 60 kHz, respectively), which showed different outputs, depending on which row was pressed. This demonstrated the high frequencies’ inability to detect changes in capacitance further away in the transmission line. A similar identification procedure could be performed on the X-layer to determine the column of the press. Combining the outputs in these two directions allowed nine regions of the sheet to be identified.
Figure 6-10: (a) The specific row can be identified by comparing the relative capacitance change in the Y-layer at all three frequencies. (b) A similar process can be performed on the X-layer capacitances to determine which column has been pressed. (c) Combining the row and column data allows the sheet to recognise nine distinct keys.
6.5. Discussion

The 3x3 results demonstrated the ability to significantly increase spatial resolution by implementing the multi-frequency method on different sensing layers. Prior to this work, most large scale systems required separate sensors and wires to detect changes at different positions. This significantly increased the complexity and cost of systems with large numbers of sensors. We achieved the same result using a single DE sensor and a multi-frequency capacitance sensing approach.

Using the DE’s high resistance electrodes as a transmission line, we were able to target specific regions in the sheet. The sheet was made from a single laminated structure and the electrodes for the two sensing layers were oriented orthogonally. This coupled the deformation of the two sheets together, but maintained their electrical isolation.

Although, theoretically, there is no limit on the number of positions into which the sheet can be subdivided, each additional sectioning reduces the area of each section and, hence, the difference in capacitance between the two adjacent frequencies. Eventually the capacitance change will fall under the noise floor of the system, and thus a practical limit is imposed. One way to reduce noise is to add extra shielding layers on the outer electrodes as discussed in the previous chapter to prevent stray capacitance coupling.

The FFT algorithm allowed multiple frequencies to be calculated simultaneously, thereby preventing any time lapse errors. It also acted as an inherent band-pass filter since it separated the response into different frequency components. This eliminated the creep of noise from non-relevant frequencies into the signals of interest. Further improvements in speed can be achieved by implementing the FFT procedure in hardware.

6.6. Chapter summary

Stretchability is a property that unlocks great versatility and design freedom. A soft, flexible and stretchable sensor sheet was made from a dielectric elastomer. By using multiple sensing frequencies on different layers, we showed how to detect pressure in two dimensions. This has various applications ranging from the creation of touch interfaces to mapping foot pressure inside a shoe.

By adjusting the sensing signal with multiple frequency components, we can also reconfigure the sheet for different layouts and increase the number of keys without adding any additional wires or hardware. This brings us a step closer to the effective design of a motion capture suit.
Conclusions and outlook

Next time you’re on the golf course and about to take a swing, consider for a moment what your body position and technique looks like. Motion capture can provide us with powerful insights, allowing us to prevent injury, improve performance, speed up recovery and even to sense our mood and emotions. The motivation behind this thesis was to take motion capture out of the studio so that it could be seamlessly integrated into our daily activities (Figure 7-1). The approach taken was to develop the sensing technology for a promising soft, wearable motion sensor: the dielectric elastomer. A number of key challenges were addressed in this work including improvements in sensing efficiency, accuracy and large-scale scalability.

Figure 7-1: The motivation of this thesis was to develop wearable motion capture sensors so that we can freely and unobtrusively capture the incredible mobility of the human body. (Image from [156])
7.1. Thesis summary

This thesis began with an analysis of camera-based motion capture systems for recording our body posture, technique and motion in everyday life. While camera-based systems have been labelled the gold standard in terms of accuracy and resolution, they have a number of key limitations preventing their usage outdoors. These include high setup costs, powerful processing requirements and limited portability. A practical alternative for recording our body motion in a wide variety of environments is to embed motion sensors directly into our clothing or to incorporate them into wearable attachments.

Chapter 1 reviewed some potential sensor candidates including inertial measurement units, liquid metal strain sensors, ionic and hydrogels, piezoelectric, piezoresistive and piezocapacitive fabrics and elastomers. These were evaluated against different performance criteria: accuracy, resolution, versatility, comfort, safety and scalability to large numbers. The conclusion drawn was that the ideal sensor is one that can measure body motion with a high level of accuracy, is non-obtrusive, allows natural movement, is robust enough to handle any unexpected falls or collisions, and is scalable to the measurement of a large number of regions.

While no sensor candidate completely satisfies all of these criteria, the piezo-capacitive dielectric elastomer (DE) provides a promising solution. DEs are soft, flexible and stretchable multi-functional transducers that can be made into a sensing skin. In Chapter 2, we reviewed the different materials, configurations and sensing methods available for DEs. A key challenge limiting the large-scale implementation of DEs as motion capture sensors is the lack of scalability in capacitance sensing methods. This is due to non-ideal electrode characteristics such as high resistance and variable strain-dependence. Most conventional capacitance sensing methods lack the ability to handle these characteristics and are unable to accurately measure the capacitance of the DE.

On the other hand, the traditional methods that do work were mostly designed for ‘self-sensing’ applications where the DE is simultaneously actuated under high voltage and sensed. These methods often use large, bulky electronics and lack the energy efficiency and safety features required of wearable sensors. The goal of this thesis was to develop new low voltage capacitance sensing methods that are efficient, accurate and highly scalable.

Chapter 3 began with the design of a low voltage, multi-channel hardware architecture based on the Hyper-plane capacitance sensing method. This architecture was capable of achieving a 20Hz feedback rate for eight independent low cost carbon-based DEs with a 0.1 pF resolution. This sensing unit, dubbed “The OCTOSENSOR”, was used by other researchers from the Swiss Federal Laboratories for Materials Science and Technology and the Université de Sherbrooke in related applications.
Next, we looked at simplifying the capacitance algorithm. We introduced a sensing circuit that could calculate capacitance locally in hardware and output the capacitance as an analogue voltage. This reduced the computational load and freed the processor to perform higher level functions. Our new method, termed ‘Charge Tracking’, uses the movement of charge on the DE to track changes in its capacitance. This improves efficiency by eliminating unnecessary switching losses when the DE is used in applications which require the monitoring of slow movements such as sleeping posture. Our method can be implemented using simple, readily available circuit components and is the first to use a DC voltage as the sensing signal.

Another challenge in adapting DEs to measure human body movements is the number of distributed electrodes required to cover a large surface area. This can present new challenges as the non-ideal characteristics of the electrode and interconnects are amplified. Chapter 4 detailed, for the first time, the ways in which high sensing frequencies can miscalculate the capacitance as they violate the lumped parameter assumption. This often results in the measurement of a lower capacitance than expected. A transmission line model was used to simulate this effect and a guide for the selection of an appropriate sensing frequency was presented.

The frequency dependency of capacitance was an important discovery that gave us the ability to sense different positions within a single sensor. Chapter 5 modelled the transmission line with different levels of electrode resistance and demonstrated that it could have a strong effect on the transmission of the sensing voltage. It showed that high sensing frequencies suffered strong attenuation as a result of the highly distributed resistance in the electrodes. By comparing the capacitance measured at different frequencies, we were able to localise capacitance changes inside the DE.

Our multi-frequency localisation technique provided the first method for determining local deformation within the DE. It was an important step forward in improving scalability by reducing the number of discrete sensors, wires and sensing electronics. The result simplified large sensing systems with multiple degrees of freedom. As an application, we developed a soft touch musical keyboard which used a single DE sensor to sense presses in multiple regions.

We extended our localised sensing technique to the differentiation of strain in two dimensions by incorporating two separate sensing layers with their electrodes oriented orthogonally on separate layers. Chapter 6 described the development of a 2D sensor sheet that can be used to create a touch keyboard with multiple regions. The sensor could be electronically programmed to increase its resolution. This was demonstrated by adding a third frequency component to the sensing signal which increased the resolution of the sheet from a 2x2 array to a 3x3 array. A new Fast Fourier Transform technique was presented which enabled the efficient calculation of capacitance at several different
frequencies simultaneously. This improved the speed and accuracy of the sensor, thereby preventing the occurrence of any time lapse errors.

7.2. Major contributions

**Chapter 3:**

- ✓ Low voltage implementation of multi-channel hardware for the Hyper-plane capacitance sensing method.
- ✓ Presentation of ‘Charge tracking’ capacitance sensing method that uses a DC voltage as the sensing signal and determines capacitance of low cost carbon-based DEs locally in hardware to reduce computational load and improve efficiency.

**Chapter 4:**

- ✓ Identification of capacitance frequency dependency for DEs with large surface areas. A high sensing frequency can underestimate the true capacitance of the DE.
- ✓ Provision of a transmission line electrical model and design framework for choosing an appropriate sensing frequency.

**Chapter 5:**

- ✓ Modelling of the DE transmission line to show how local capacitance changes can be differentiated using signals of different frequencies.
- ✓ Demonstration of localised capacitance sensing in a musical keyboard made from a single DE sensor with the ability to differentiate touch in four different locations

**Chapter 6:**

- ✓ Localisation of sensing in two dimensions using two sensing layers with orthogonal electrodes.
- ✓ Presentation of a Fast Fourier Transform method that can simultaneously determine several capacitances, thereby improving speed and accuracy.

7.3. Concluding remarks: to infinity and beyond

Motion capture has allowed us to quantitatively record our body movements for analysis and feedback. Over the years, it has seen numerous uses in movies, animations, video games, sports training, coaching, health monitoring, rehabilitation and interactive motion controls. Now, with advances in smart materials such as the dielectric elastomer, we can finally extend this technology to freely and unobtrusively capture our movement anywhere, and at any time (Figure 7-2).
By integrating smart DE sensors into clothing and wearable garments, we will be able to gain new insight about how we are moving in new conditions and during activities. For athletes, this will enable real-time feedback for performance improvement. For patients recovering from injuries or suffering disabilities, this can provide early fault detection and corrective gait training. For gamers, this will allow new interactive controls for playing video games. Other applications include the ability to communicate with each other using body gestures or detecting drivers who have fallen asleep at the wheel. Wearable motion capture sensors will undoubtedly provide an endless array of applications.

Although the results of this thesis have brought us a step closer to this reality, there are still a number of challenges that need to be addressed. These will require further developments of materials, sensing electronics and data processing.

On the sensor side, the development of more homogenous materials to create better repeatability is required. This will reduce the need to calibrate each sensor individually before use. Second, we require automated manufacturing processes that can be scaled to large quantities. All of the DE sensors developed for this thesis were made by hand, a time consuming process.

Further research also needs to be conducted on wearable attachment designs that prevent mechanical slip as this is one of the main sources of error. In addition, better techniques for shielding the sensor from stray electric fields need to be developed in order to prevent the human body’s capacitance from interfering with the sensors’ capacitance measurements. Our preliminary experiments show that adequate shielding can be achieved using additional grounded outer electrode layers. Finally, further development is required to embed DE sensors directly into our clothes.

Much of the work in this thesis has focused on improving the efficiency, accuracy and scalability of capacitive sensing methods for DEs. While there are still many optimizations that can be made, one
particular area of improvement would be to miniaturize the sensing electronics so that they could be incorporated into a more wearable form-factor. Additionally, the development of more flexible and stretchable electronics would make the entire sensing system soft and compliant. There have already been promising developments in this area as DE materials have been used to create electronic components such as digital switches, logic gates and even a rubber computer [158], [159].

This thesis has contributed to the front end of this challenge by making DE sensing systems more efficient, accurate and scalable. However, capacitance is still just raw data. It is only useful if we can make sense of our behaviours and patterns. For this, we need intelligent algorithms to analyse and identify the drivers behind our body motion. Only once this goal has been achieved can we truly use motion capture to improve and enhance our lives.

7.4. Related publications

First authored publications:

Journal articles


**Conference papers**


**Patents**


**Co-authored publications:**

**Journal articles**


**Conference papers**


**Book contribution**

References


[48] F. Carpi, D. De Rossi, R. Kornbluh, R. Pelrine, and P. Sommer-Larsen, Dielectric Elastomers as


Volume 22, Issue 1, Pages 015002, 2012.


