Differentiation and classification of different materials on a touch-screen using a piezoelectric contact microphone

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Abstract

In this report, a potential improvement of an optical touch screen solution by means of acoustic sensing is presented. The goal is to utilize the different vibration patterns that arise when different materials touch the screen to be able to identify them. This identification of different materials opens up new opportunities to give input to the touch-device which could potentially replace menu bars or touch-and-hold interaction that exists today. The ability to discriminate between object also gives the opportunity for different objects to represent different things, such as colors, tools or unique users. A piezoelectric accelerometer is used to collect the sound signals, which are then classified using the K-Nearest-Neighbour method to identify which material that touched the screen. The result shows that the classification for three different objects was done with a 96% correct classification. If only two different pens are used, the correct classification goes above 99%. The report further describes some of the key factors that needs to be taken in account when developing such an acoustic sensing system, such as force, distance and location of the taps on the screen. Those factors does all seem to alter the frequency spectrum in some way.

Preface

This thesis work is done at FlatFrog laboratories located in Lund during first of February until last of June 2016. The purpose of the thesis work is to investigate the possibilities to distinguish between different objects that touches a large touch-screen monitor and to look into the possibilities to complement an optical touch solution with a vibration sensor.

I would like to express my thanks to my supervisors Frida Sandberg at the institution for biomedical engineering and Kristofer Jacobson at the signal processing deparment at FlatFrog. I would also like to thank Hans W Persson at the Electrical and information technology department for his help in the sensor area. Thanks to Richard Brown at Measurement Specialities for donating the ACH-01-03 sensor with complementary amplifier box. I would also like to thank Nicklas Ohlson, Magnus Thulesius and Martin Trobäck at FlatFrog for their assistance during this project, and thanks to all other employees at FlatFrog for providing a welcoming and warm atmosphere.

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Chapter 1
Introduction

The technology used in the smart touch-screen devices today have become advanced and can perform a versatile amount of different tasks, such as communication, navigation, presenting results and data, collecting data in their environment and much more. There is, however, a great limitation in the way humans can interact with the touch-screens. Some touch-screens today has come as far as multi-touch, sensing more than one object at a time, but one thing that has been lacking is a way to differentiate between different kinds of objects. Such an additional dimension could prove to be useful in many ways. Having different kinds of objects to have different meanings gives the ability to use different physical objects for different options such as copy/paste, different colors and more. It can also aid rejection of unwanted touches and improve the amount of false positives events.
The idea with this project is to enhance an optical touch system to capture information about the type of object in addition to its position. The goal is to investigate the possibility to enable new potential interactions with the touch screen by adding an acoustic sensor to the touch system. Object differentiation could potentially replace some of the existing interactions found on most touch screens today such as touch and hold, double taps and menu bars, to instead use different kind of objects to give the same options. It can also help solve the problem with so called palm rejection. The problem in palm rejection is that when a user writes something on the touch screen the user often rests their hand on top of the screen, which leads to unintentional interaction since the touch screen detects all sorts of touches. If there is a feasible way to discriminate between the touch that originates from the skin of the touch from the palm and the object, i.e. the pen being used to write with, this would be helpful to give the option to ignore the palm touch while the pen is being used. Microsoft have made an effort to solve the palm rejection problem by simply regarding touches with a large contact area as unintentional [1]. FlatFrog however uses the large contact area to be interpreted as an eraser instead, and thus wants to find an additional solution to this problem. If an acoustic sensor could detect that a pen and a hand touches the screen at the same time, this information in addition to the location of the touches could be a solution for the palm rejection problem.
There are examples of various ways for object differentiation done today. One way is to use active pens, pens with some integrated electronics, that send out a signal telling the screen which object that touches the screen. These pens are

limited by the frequency bands they need to use and also have a higher production cost compared to a passive pen. Other methods base object recognition on some sort of optical reader or camera to discriminate between different objects. A third option for the object recognition is discrimination based on the size of the object. It would however be favorable to be able to discriminate objects based on their vibration pattern instead because it would not force a certain size of the object to be used which limits the design freedom. Compared with the active pens, a passive pen can be made much cheaper and does not need energy or signal transmission.

This project aims to find a solution for a touch-screen device to distinguish between different passive objects based on the vibration pattern that results from the objects contact with the touch-screen. In this study, five different experiments were conducted to get a better understanding of how well an acoustic sensor can be used on a glass touch screen of larger scale, and a study was made to get an estimate of how well differentiation could be made. A literature study was conducted to find out what previous researches had done in the field, and to find out which type of sensor that would be favorable to use.

1.1 Disposition

First a review of previous papers is given in the background, chapter 2, followed by a theory section that deals with acoustic signals, sensors and touch screens, 2.2. After this the materials used is described in chapter 3 and the different experiments conducted will be described in the method, chapter 4, followed by the results of said experiments, 5, and a discussion about them, 6.

Chapter 2
Background

In this chapter, previous work will be reviewed and theory regarding materials and signal processing tools used will be described.

2.1 Related Work

This thesis work is not the first to investigate how the vibration pattern looks when a glass pane is tapped by different objects while a vibration sensor is measuring the signal. Paradiso et.al investigated if piezoelectric contact microphones mounted on a glass pane can be used to differentiate between the touch of a knuckle knock, a bash with the fist and a metal object touching the screen, with the goal to make interactive glass surfaces, e.g. shop windows [2]. To differentiate between the metal object and the knuckle taps, Paradiso et.al uses the frequency spectrum where the metal object produces much higher frequency components than the knuckle tap. To detect the fist bash, a specific transducer is adhered to the glass pane that responds strongly to the low frequency signal that arises as a result of the fist bash.

To determine the frequency of the signal, Paradiso et.al did not use the Fourier transform, but rather looked at the number of times the waveform crossed zero during a fixed interval to reduce computational complexity, which made it possible to be a fully hardware solutions without computer calculations. To make this measurement even more reliable, the differential time for the signal to reach sensor pairs was also used, since the metallic impact has a higher propagation velocity than the knuckle taps because of dispersion. In the paper, the position of the knock was also tracked, and stated to be within 20 cm of the actual touch. The study concludes that it was possible to differentiate between the three different touches, but that it was "hits rather than touch" required and with a latency of 65 ms.

Lopes et.al searches for a way to sonically enrich touch surfaces to make it possible for the user to express a larger amount of different actions [3]. A sonically enhanced system is proposed where the characteristics of amplitude and spectrogram (timbre) is investigated to be used as source for the differentiation of touches. In their case, the goal is to differentiate between various types of touches with the hand: punch, fingertip, knock and slap. To discriminate between those types of touch, fundamental frequencies for the different sort of touches are used. It is stated that

the finger has fundamental frequencies at 38Hz, 120Hz and 960Hz while the knock has fundamental frequencies at 40Hz, 110Hz and 5KHz, which suggest that the sensitivity in the frequency spectrum needs to be quite high for this discrimination. Another of the points made is that the acoustic input system in addition to the touch solution would unlock the possibility to interact with the touch device on its bezel or back and thus expanding the interactive area. No values on the amount of correct classifications are given however.
Harrison et.al looks at a way to acoustically differentiate between different parts of a finger, and to discriminate between different types of pen in a project called "TapSense" [4]. In the study it is stated that the differentiation "...relies on the physical principle that different materials produce different acoustic signatures and have different resonant frequencies", much like the aim of this thesis work. The goal is stated as segmentation and classifying sounds resulting from the objects impact with the screen. The result of the classification is stated to be $> 99\%$ correct classifications if exactly two different objects is used, while the correct classification is reduced to around 95% if four different objects are in use at the same time.

In the paper, the features that are used are different frequency properties and different amplitude properties. The frequency band being used ranges from 0 to 10KHz. In the study, the total time from impact to classification is stated to take about 100ms, which makes it possible to implement in a real-time process. The sampling rate is set to 96KHz and the sampling time 43ms.

In the study they have made, the computer was trained both specifically for one user since different people have different anatomy of their finger and also different behavior when tapping the screen, but also with a general classifier. As expected, the general classification had a higher error rate than the user specific. A support vector machine is used for the classification, after they have done the feature extraction.
There is a company called Qeexo, founded by one of the authors of the last mentioned paper, Chris Harrison, that looks into the matter of differentiation between objects, or rather different part of the same object, based on the vibration pattern that arises when the object touches the screen. In the patent US9013452 B2 filed in USA 2013, a method to differentiate between fingertip, knuckle or nail using acoustic signals is protected. The patent does not go into detail about how the differentiation is done, but on Qeexos' webpage [5] it is stated that the accelerometer integrated in smart-phones today is used and that Qeexo provide software that enables the differentiation of those different parts of the finger.
Another way to use an acoustic sensor in combination with a touch screen is mentioned in another paper by Harrison et.al [6]. It is proposed that "acoustic barcodes" can be produced and placed on a surface. Those barcodes would each have their own unique signature sound they make when scratched. When those barcodes are scratched it is possible to detect via a contact microphone which object that was scratched based on the sound it made. This means that there could be "buttons" in form of such barcodes placed on the bezel of a screen which are activated by being scratched.
In yet another paper by Harrison the possibility to distinguish between different shapes drawn on a surface is investigated [7]. This could prove useful when writing

specific letters, like the 'i' or 'y'. The lower case 'i' could easily be interpreted as an upper case I on a touch screen, and the 'y' could very well be a 'v' with a line under that is separated with a small gap. A system that uses a sound system in addition to another touch detection could be able to separate the dot over the 'i' or connect a broken 'y' more easily. The double tap is another "gesture" that could be detected with the help of the acoustic sensing system, as a double tap can easily be missed if it occurs to fast or the tip of the pen is not lifted high enough for the touch detection system to notice.

The previous work has proven that it is possible to recognize different kind of materials based on the acoustic pattern made by their impact with the screen, even though not every paper gives numbers on how well this recognition is made which makes comparison a bit tricky. Another thing that makes it hard to compare the different results from the studies with each other is because there are also a lot of factors that can make the differentiation easier or harder, such as the type of material used, the size of the screen and the force of the impact. The paper by Paradiso et.al mentions that hits rather than touches was required to detect the sound signals [2]. In this thesis work, such factors will be investigated, and an estimate about how well the classification can be done will hopefully be achieved. Focus in this report will be to make the classification of objects on relatively large screens.

Something that all the papers agrees about is that a piezoelectric contact microphone is the best kind of sensor for this application, and that the best way to classify the different types of materials is by means of their frequency components that originates from their impact with the screen.

2.2 Theory

2.2.1 Touch Screens

The most common type of touch screens used today is the capacitive touch screen, which can be found in almost every cellphone these days. The capacitive touch screens have a two dimensional grid of electrodes covering the screen over which a voltage is applied. When a finger or conductive stylus is brought close enough to the screen the electrodes capacitance changes and can be detected, and by measuring all electrodes capacitance changes the location of the touch can be found. There are two types of capacitive screens: self-capacitance- and mutual capacitance screens. The mutual capacitance screen has the possibility to detect multi-touch, while the self-capacitance sensor has better accuracy of detecting touches further away from the electrodes [8].

Optical touch screens

The touch screen solution that FlatFrog uses, which the acoustic sensing system is supposed to be used together with is an optical touch screen solution. Light is injected on one side of the screen and extracted at the opposite side. Through the glass the light is transported by total reflection. When an object touches

the surface some light will scatter from its original path which is detected by the receiver at the other side of the screen. This means that the object that touches the screen does not need to be conductive since it is the different refractive indexes between the glass and the material touching it that will distort the total reflection in the glass. This mean that any sort of materials can be considered to be used for the acoustic sensing system. The optical touch screen solution has several advantages compared to other touch screen solutions. One of the most important ones is perhaps that no part of the sensor system needs to be between the touch surface and the display, which makes it possible to have a very high display quality, and it also makes it possible to have a transparent screen. Due to the fact that only the perimeter and not the whole area of the screen needs to have the sensor system the cost for this technology scales linearly instead of growing quadratically with increased size of the screen which makes this technology perfect for screens of large size [9].

2.2.2 Acoustic attenuaton

According to the theory the sound signal is attenuated while it is travelling through the glass. The further distance it travels the less amount of the original energy will reach the sensor. Different frequencies are attenuated differently while they are travelling through a medium. The main attenuation factor is attenuation due to internal friction in the medium which means that the energy of the sound wave is converted into heat. But the attenuation of sound in glass is complex, factors such as the topology of the glass, its internal friction and its temperature can change the amount of attenuation of certain frequencies in the glass [10]. There are many different models that look at the acoustic attenuation in the glass. One of the most simple one is described in a paper by W. Chena et.al where mainly the losses due to friction is considered [11]. The time it takes for the sound wave to dissipate in the screen is also dependent on the size of the screen. It takes a longer time for the sound to dissipate in a screen of larger size, which is mentioned in "Tapsense" and which also the findings of this report supports [4]. When the sound wave have not been fully attenuated, the sound wave of the most recent impacts will still be present in the glass and interfere with subsequent impacts. This means that if the taps come close to each other in time, they will be harder to discriminate from each other than if the taps are made one at a time with enough time to let the sound wave dissipate.

2.2.3 Harmonic periodic wave motion

A mechanical system set in motion will begin to oscillate periodically. The real valued solutions, which are the interesting ones in this case, by the oscillating system can be written as

$$Y = A * \sin(\omega * t + \alpha) \tag{2.1}$$

where A is amplitude, ω, frequency constant and α is a phase constant. If the system can be described as a single sinusoid function it is said to have a simple harmonic oscillation pattern. Most mechanical systems have several resonant frequencies, a fundamental resonant frequency with harmonics, which is the case

with the touch screen since it is not only one material resonating, but the frame around the glass will also oscillate together with glass and the material touching the glass. In the solid materials there are also transversal and longitudinal waves that occur simultaneously, and is harder to describe mathematically [12]. The fact that the signal that arise from the impact of the material with the touch screen is a combination of oscillating systems means that the features that can be used are resonant frequencies, amplitude or variations of these such as differential amplitude at different times i.e. dampening.

2.2.4 Fourier transform

The sound signals can be seen as periodic sequences $x(n)$ as a result of the oscillating system set in motion by the materials impact with the glass, with a period N, discrete since it is digitally sampled,

$$x(n) = x(n + N) \tag{2.2}$$

for all n.
The Fourier series representation of $x(n)$ can be written as

$$e^{j2\pi kn/N}, k = 0, 1...N - 1 \tag{2.3}$$

and is expressed as

$$x(n) = \sum_{k=0}^{N-1} c_k e^{j2\pi kn/N} \tag{2.4}$$

where c_k are the coefficients in Fourier series representation [13].

The discrete Fourier transform (DFT) for transforming the sequence $x(n)$ into a sequence of frequency samples $X(k)$ is given by:

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{j2\pi kn/N}, k = 0, 1, 2..., N - 1 \tag{2.5}$$

by means of this transformation the signals can be studied in the frequency domain [14].

2.2.5 Statistical tests

To find out whether an experiment yields significant results, statistical tests can be conducted given that the data set is large enough to be able to apply the statistical test. Two common statistical tests are tests with confidence interval and tests with a test-unit (sometimes called t-test because the test unit is called T, or P-value test since the result of the test will have a value P which shows the level of significance).

In a confidence interval test an observed value θ, with a mean from several observations $\bar{x}$ with some variance δ and that originates from some distribution X, is compared to another value θ_0 to see if the two observations originates from

the same distribution. Usually a 95% confidence interval is chosen, which means that if the test shows a significant difference there is at least a 95% chance that the different observations originates from different distributions.

The interval looks as follows:

$$I_\mu = (\bar{x} \pm t_{((1-0.95)/2)} * d(\bar{X})) \tag{2.6}$$

where $\bar{x}$ is the mean of the observations, $t_{((1-0.95)/2)}$ is the 95% quartile of the t-distribution and $d(\bar{X})$ is the mean error, calculated as the standard deviation of $\bar{x}$ divided with the amount of observations, n:

$$d(X) = \delta/\sqrt{n} \tag{2.7}$$

Instead of making a test where the significance level is chosen beforehand such as the confidence interval test, the test-unit hypothesis test can be used, which will result in a P-value which describes the level of significance. A test unit T is calculated as

$$T = \bar{X} - \mu_0/d(\bar{X}) \tag{2.8}$$

where μ_0 is the mean value of θ_0.

The resulting value is referred to as the P-value, and shows the distance, in terms of probability, between θ and θ_0. If $P > 0.05$, the result is not significant [15].

2.2.6 Feature extraction

Features are some sort of characteristics that can be used to describe an object. By segmenting out some specific attributes for a number of different objects, a set of features which describes the objects is made. The attributes used in this work to describe the signals can be amplitude of the signal and the power in different frequency bands. A good feature is a feature which will always be the same for the same object while it is different from the same attribute of other objects. Feature extraction is thus a way to capture those specific attributes that can be used to describe an object and then put some sort of comparison label to it such as numbers. Different approaches could be used when extracting features for the different materials. One way to do it is to use a general approach where in this case the whole frequency spectrum is divided into blocks of a certain size. A good classifier will then find the differences apparent in the features based on this frequency spectrum. A general classifier has the advantage that it can handle any type of new material that is introduced to the system. One disadvantage is that the computational complexity is increased. Another way for the feature extraction is a method where the objects that will be classified are already known, and the feature vectors can be tailor made to capture those exact objects.

2.2.7 Classification

Classification is a process where observations are identified and differentiated to give them a certain class. If the classification is done by means of supervised learning the new observations will be classified based on a set of training data,

which is the case used in this thesis work. The training data is a set of data where the ground truth for the data is known, and a supervised machine learning technique uses this data for training. When a test set of data is introduced to the algorithm, the test set will be classified by the algorithm based on the data in the training set.
If the classification is made unsupervised, the algorithm will decide an amount of clusters for groups of data which is significantly different from each other. New observations are then fit into different clusters.

Decision tree

The decision tree is a recursive classifier with a branchlike structure with a root, nodes and leaves. In each node a decision is made for which branch that should be traced based on the values of the feature vector provided. The leaves of each node represents a class. New observations are placed in the leaf with the most appropriate target value. When a new observation is made, it is navigated through the tree from the root down to a leaf. In this way the new data is divided into classes. An example of a simple decision tree is shown in figure 2.1.

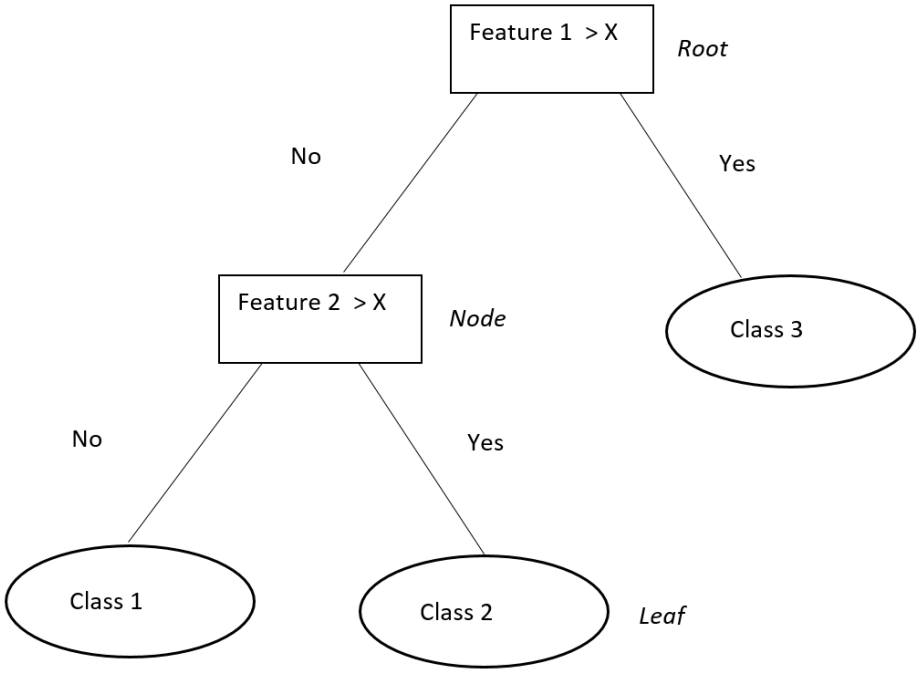

Figure 2.1: An example of a simple decision tree

K-nearest neighbours, KNN

With the K-nearest neighbour classification the observations are clustered in a N-dimensional space with a number of classes, where N is the number of features used

and K is the number of neighbours used in the algorithm. The algorithm consist of two main parts, training and classification of new elements. In the training phase the algorithm is fed data where the class is known for the feature vectors provided. In the classification phase, new elements are given a class dependent on its K closest neighbours, where K is a number chosen by the user. It is common that the classification is based on majority voting, i.e. the highest amount of neighbours of a certain class among the K nearest will decide the class of the new elements. Another common approach is to give weights to the neighbours so that a close neighbour will count higher than more distant ones. Closest neighbour is usually the points in the feature space to which the euclidean distance or squared euclidean distance is minimized. In figure 2.2 the triangles and the circles represents data points in the training set. Based on those training points, new points will be assigned as either a circle or a triangle based on its position in the room spanned by the feature vectors. In this two-dimensional example seen in figure 2.2 the new observation, marked as a question mark, will either be classified as a triangle or a circle. If only one nearest neighbour is used it will be classified as a triangle, while it will be classified as a circle if k is equal to three.

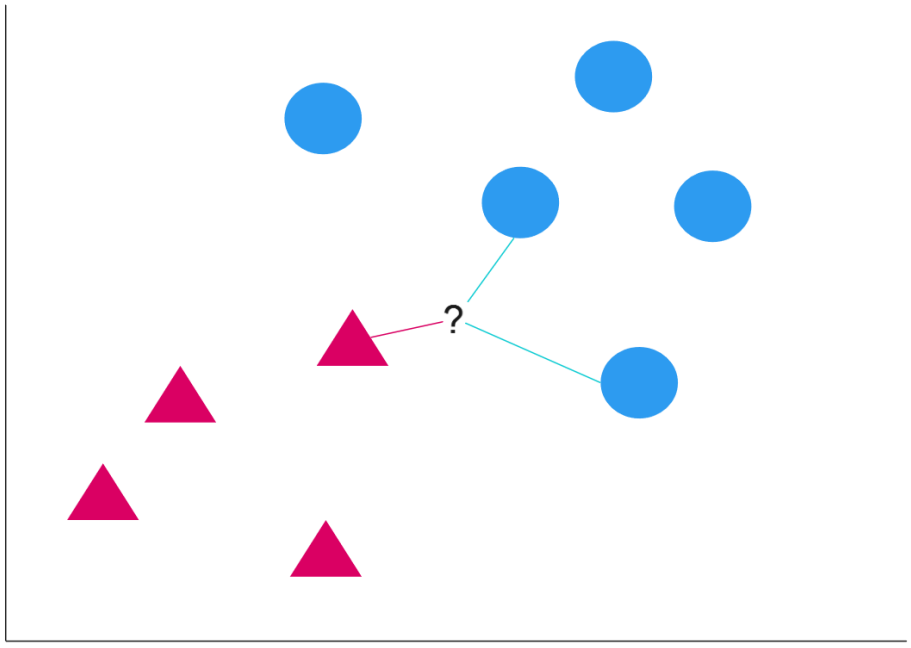

Figure 2.2: An example of classification with the K-nearest neighbour method.

Chapter 3
Material

3.1 Accelerometers

An accelerometer is a type of sensor that measures acceleration. The two most common types of accelerometers are microelectromechanical sensors (MEMS) and piezoelectric sensors. In the micromechanical sensor a cantilever is bent by its inertia when the sensor is subjected to an acceleration, and the bending of the cantilever is proportional to the acceleration [17]. A piezoelectric sensor uses a phenomena found naturally in some types of crystals: when a piezoelectric material is subjected to mechanical stress, an electric polarization is produced. Piezoelectricity follows a linear relationship between electrical and mechanical interaction processes, and it is thus possible to determine the speed and force of a vibrating material by measuring the voltage over the piezoelectric crystal [18].

The handbook "Piezoelectic accelerometer and vibration preamplifier handbook" [20] describes the piezoelectric accelerometer as the most reliable, versatile and accurate type of sensor for vibration sensing on a surface. This is mainly because the piezoelectric accelerometer can be used over a wide range of frequencies, and also has excellent linearity over a wide frequency range. It is also self-generating which mean it does not need an external power supply and the piezoelectric sensor is also compact and has a high sensitivity to mass ratio.

3.2 Selection of sensor

The first part of the project was to find a suitable sensor for the collection of the acoustic signals. Microelectromechanical and piezoelectric sensors commercially available were reviewed. The main aspects enquired were bandwidth, price, sensitivity and how easy they were to use. One of the difficulties when searching for a sensor was that the desired bandwidth required was unknown. Of course, a sensor with as high as possible bandwidth would be preferred as long as the additional bandwidth did not come at the expense of worse sensitivity. With a sensor that has an unnecessarily large bandwidth a low pass filter could simply be applied to see whether the same result could be achieved even with a sensor of lower bandwidth. After a thorough look at the pros and cons of the micromechanical and piezoelectric sensors it became apparent that the piezoelectric sensor would be su-

perior to the micromechanical for this application. The micromechanical sensors are much cheaper but are also much more limited in bandwidth. The first sensor that was ordered was thus the CM-01B piezoelectric contact microphone made by Measurement Specialities (MS). This sensor was cheap with an already integrated amplifier and was easy to get to plug into a BNC connector, which is a common connector type. Because of its somewhat low bandwidth, up to 5KHz, the search for a new sensor continued, and an enquiry about the ACH-01 piezoelectric sensor was sent to Measurement Specialities. After a conference call with an engineer at Measurement Specialities, the manufacturing company of the CM-01B and ACH-01 sensor, deeper insight in the sensor area was reached. From graphs over the frequency spectrum for vibration pick-ups made by three different piezoelectric sensors, the CM-01B, the ACH-01 and also the SDT1-028K, it became apparent that there was much information to be gained from the frequency spectrum above 5KHz, up to 30 KHz, which was the limit for the CM-01B originally used. The ACH-01 sensor was chosen since it had a high bandwidth, was sensitive and had a good contact surface. A piezoelectric contact microphone will be used since they pick up vibrations in the material, they are cheap enough, have a broad bandwidth and high sensitivity and do not pick up sound mediated through the air. Another good effect of the usage of a contact microphone is that the solid material has much better sound transmission properties than air which makes the microphone able pick up sounds transmitted through the solid material that we would not hear with our naked ear. In the experimental set-ups a piezoelectric contact microphone with complementary electronics to amplify the signal was used. The sensor was placed on a glass pane with an optical touch system. Two different piezoelectric sensors were used, shown in figure 3.1 where the top sensor is the ACH-01 and the bottom one is the CM-01B sensor.

Figure 3.1: The ACH-01 sensor (top) and the CM-01B sensor (bottom)

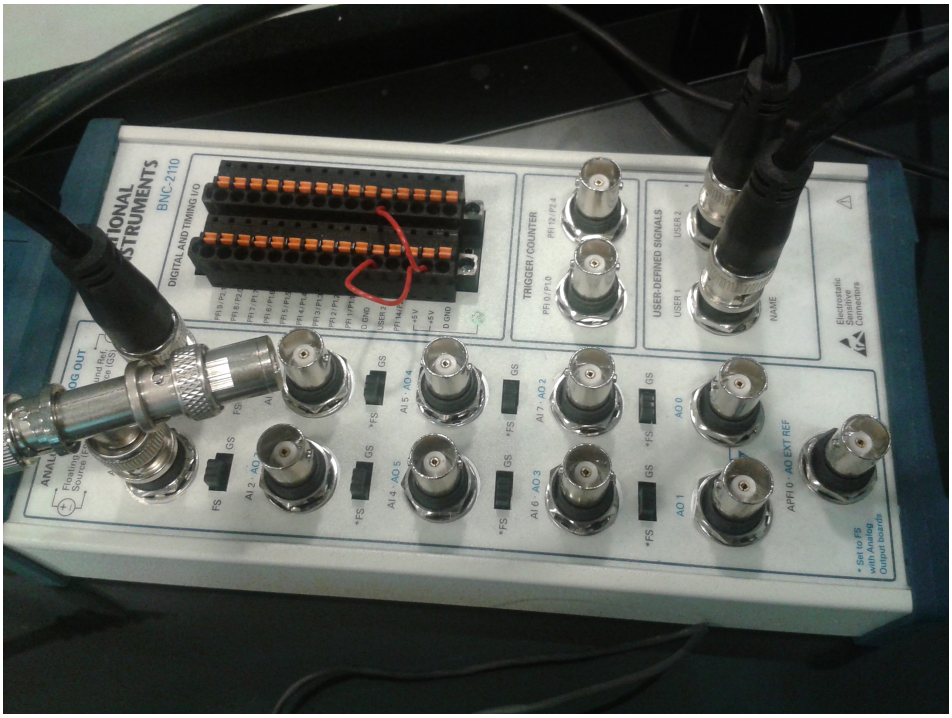

Figure 3.2: The BNC to which the sensors were connected

The glass rested on a rubber padding on a frame of aluminium. The sensor was connected to a NI BNC-2110, shown in figure 3.2, which in turn is connected to a NI-DAQ 6151 plugged into a PC running windows. On the PC, the MATLAB software is used, with the Data Acquisition Toolbox to sample the data and process it. In the figure 3.3 the FF23" glass pane with the CM-01B sensor mounted is shown.

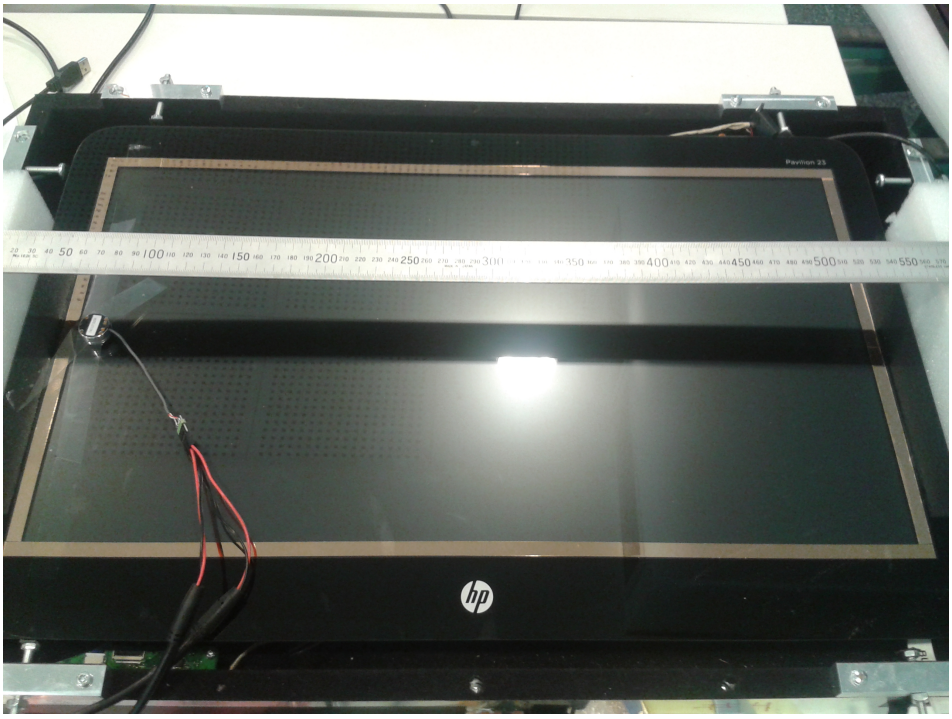

Figure 3.3: The experimental setup. In this setup the CM-01B sensor was used on the FF23" screen.

3.2.1 Sensor, position adherence

During the studies one sensor at a time was used, attached to one of the longer sides of the screen close to the edge. Optimally the sensor would be placed in the middle of the screen if only one sensor were to be used to minimize the distance the sound need to travel, and also because that is the location being used most frequently. However, if this system would be implemented in reality the middle of the screen would not be an option to place the sensor since the screen is supposed to be transparent. Instead it should be placed underneath the bezel, and hence the sensor was placed at the edge of the screen during the studies, on the glass where the bezel would be located. One problem with using only one sensor is that if the screen is large, the signal will die out before it reaches the sensor if it has to travel too far. This mean that several sensors might have to be used on larger screens if this system would be implemented in reality. To be able to change position

and to use the sensor on different screens tape was used on the top of the sensor to adhere it to the screen, both for the CM 01B and the ACH 01. According to personnel at Measurement Specialties, the CM 01B sensor were supposed to have a certain force applied to it to work as intended as it was developed to be a hand held contacts microscope. For the ACH 01 sensor, the recommendation is to glue it to the screen, but the result was good enough with the sensor adhered with tape, even though care need to be taken to see that the sensor is taped to the screen in an equal way each time it is used.

3.3 Pens used

The different materials that were used in the study were chosen due to being common and easy to find, probability to be used in a real case scenario and also because they were believed to have different acoustic signatures. The materials used are mainly wood, plastic, metal and felt, seen in figure 3.4. In a study it was stated that a Ping Pong ball would have a characteristic easily determinable frequency [19]. Tests were made using a Ping Pong ball, and it seemed to be possible to identified using a single frequency peak. The Ping Pong ball was however not so convenient to use because of its bouncing. A ping Pong ball attached to a wooden pen was also tried but it would always bounce when used on the screen. Other material that were tested included knuckle, finger and another type of plastic. Those items were rejected for various reasons, they were either to similar to some other material in terms of acoustic signature, the signal produced were to low in amplitude or were simply unpractical to use.

Figure 3.4: The figure shows the different materials of the pens that were used during the experiments. From left to right, felt, metal, wood and plastic.

Chapter 4

Method

4.1 Signal processing

4.1.1 Preprocessing

The first part of the classification of different signals is some sort of segmentation of the sound signals. To detect those events a threshold limit was applied. Once the threshold is reached an event was captured and recorded. The threshold level was set so that it would not capture noise as signals, but as low as possible to still be able to record the softest touches. After an objects impact on the screen the first 6.5ms of the signal was used for feature extraction for the classifier. In figure 4.1 an example of signals from writing on the screen with the pens of different material before the segmentation is done are shown. How a segmented part of the signal looks like can be seen in figures 4.2 to 4.4. It is in the first few milliseconds of the signal that the material specific components are most apparent before the glass begins its steady state oscillation and the material specific components are attenuated, which is shown in the results, section 5.1.1. When the signal becomes weaker, the signal to noise ratio will also go down, which means that the noise will have a larger contribution if the sampling time is extended. This means that if to long part of the signal would be used, the transient high frequency components would be vaguer. The signal will continue to linger inside the glass for about 100-150ms before it dies out depending on the force of the touch and the size of the glass. Following an event, a silent period of 90ms was used where no new events would be captured, to make sure that a following event would not be too affected by the previous tap. Also, a normal double tap took about 100ms during the study which should not be rejected by the silent period.

In the figures 4.2 to 4.4 examples of signals from taps can be seen, zoomed in at the first 100ms. The first one is made with the metal object 4.2 followed by a tap made by the wooden pen 4.3 and a tap made by the felt pen 4.4. As can be seen from the metal tap, the signal appears to contain high frequent components, which also the wooden tap does but to a smaller extent. Note that the amplitude for the felt tap is much lower, which makes the noise appear with high frequency components.

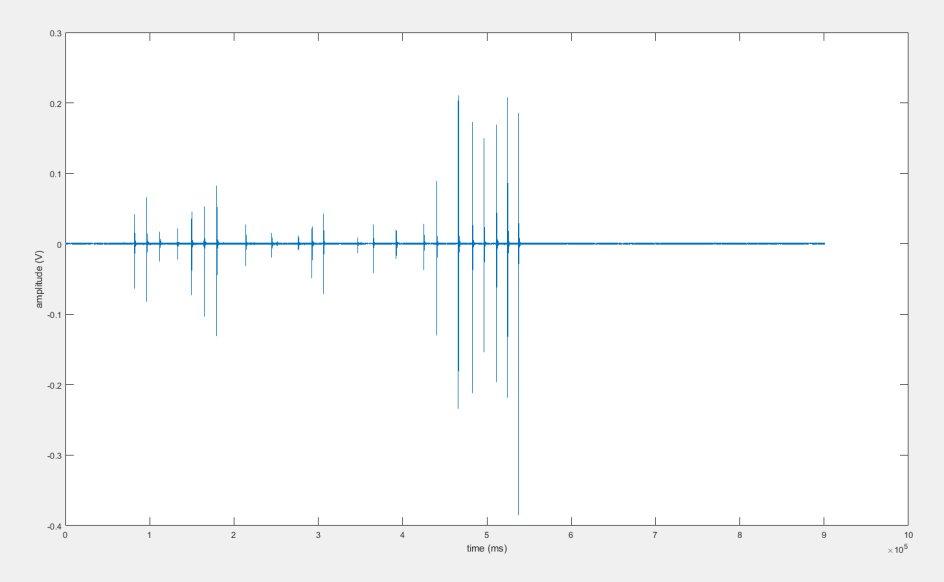

Figure 4.1: The figure shows a recording of text written on a screen before each individual event have been segmented. The writing is done by the wooden, felt and metal pens. Lines are drawn using the pens in a natural way.

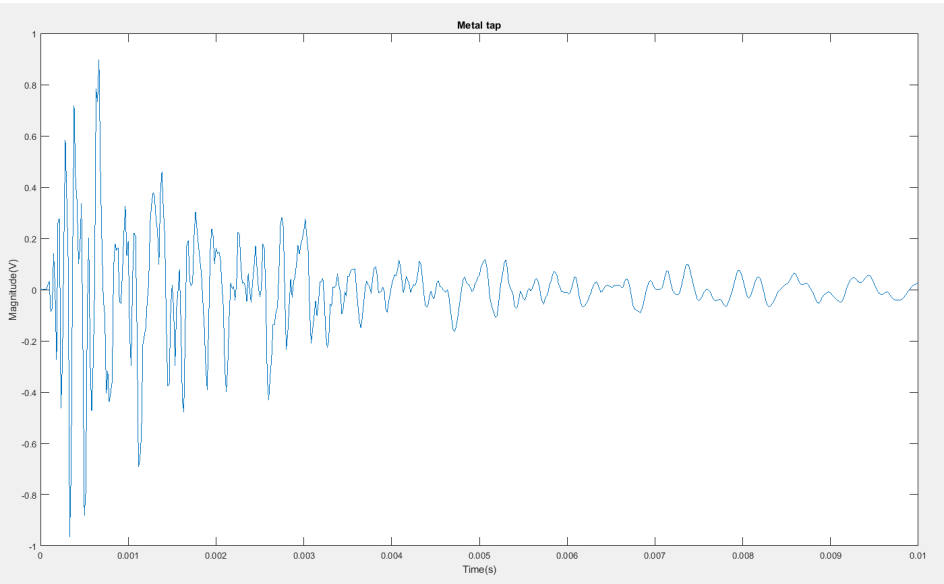

Figure 4.2: The signal of a tap made by a metal object. The signal is recorded on the FF23" screen with the ACH-01 sensor, with the tap 10 cm away from the sensor.

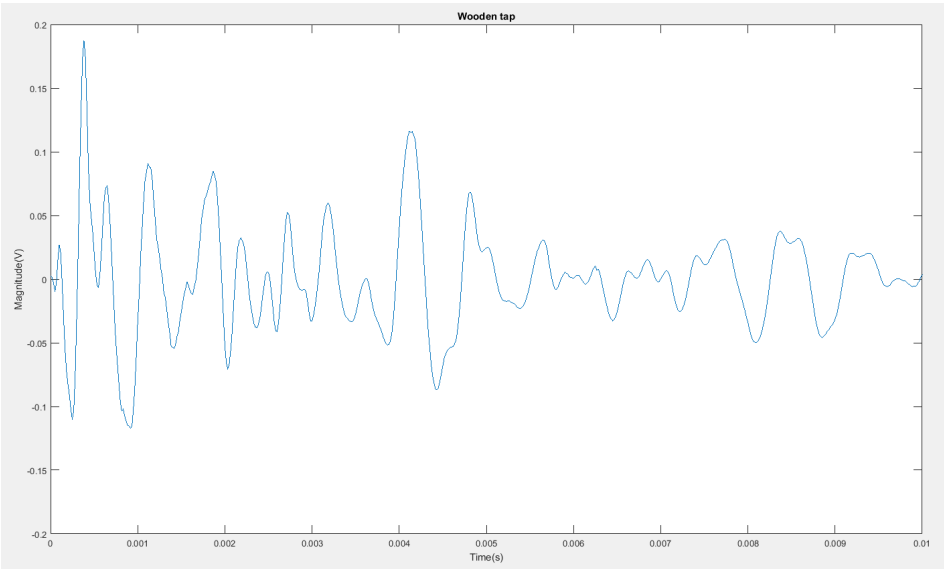

Figure 4.3: The signal of a tap made by a wooden pen. The signal is recorded on the FF23" screen with the ACH-01 sensor, with the tap 10 cm away from the sensor.

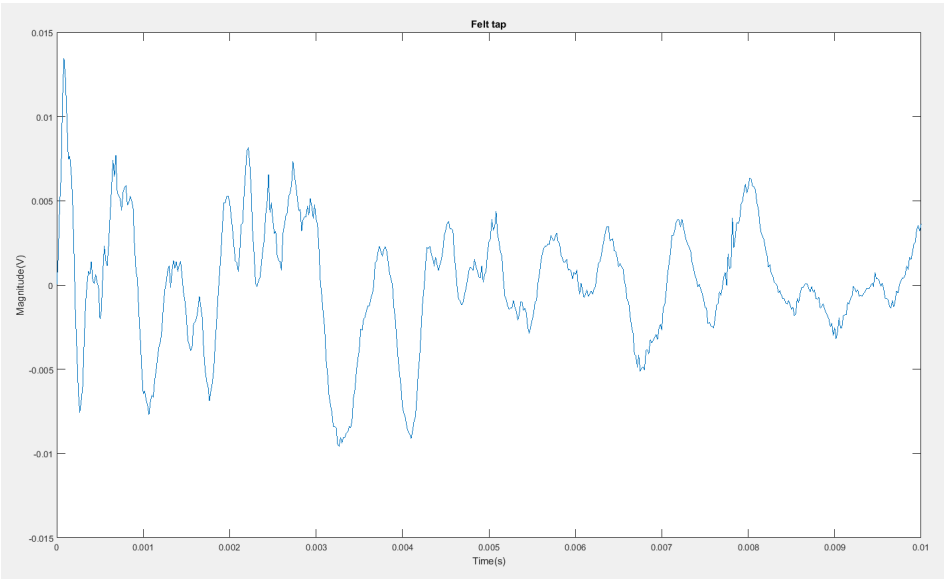

Figure 4.4: The signal of a tap made by a felt pen. The signal is recorded on the FF23" screen with the ACH-01 sensor, with the tap 10 cm away from the sensor.

To be able to extract features from the data that would be usable, the signals

was Fourier transformed, see equation 2.5, so that they could be analysed spectrally. The Fourier transformed signal was binned into bands with 50Hz in each when the CM-01B sensor was used with the signal sampled at 16KHz. When the ACH-01 sensor was used the sampling rate was 60KHz with a frequency resolution of 150Hz. Below is shown some figures of how the signal look in the frequency domain after the Fourier transform. The signals are recorded on the FF23" screen with the ACH-01 sensor, with the tap 10 cm away from the sensor. In the figures 4.5 to 4.7 examples of the power spectrum for the three materials is seen. In figure 4.5, it is evident that the metal gives rise to high frequency components. In 4.6 the power spectrum for the wooden pen is shown. It evidently lacks the high frequency components the metal object has, but it still got higher frequency components than the felt pen shown in figure 4.7.

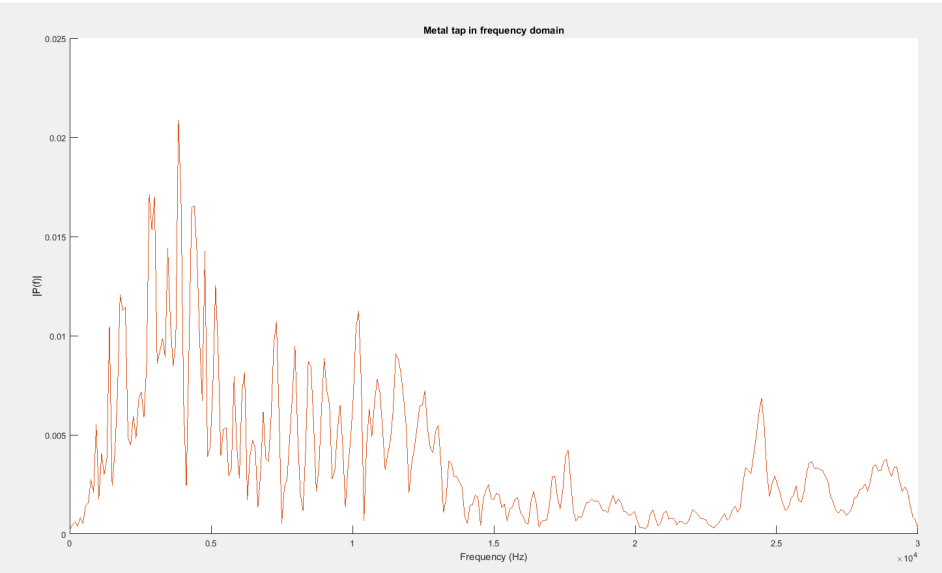

Figure 4.5: Power spectrum of a tap made by a metal object. The tap is the same shown in figure 4.2.

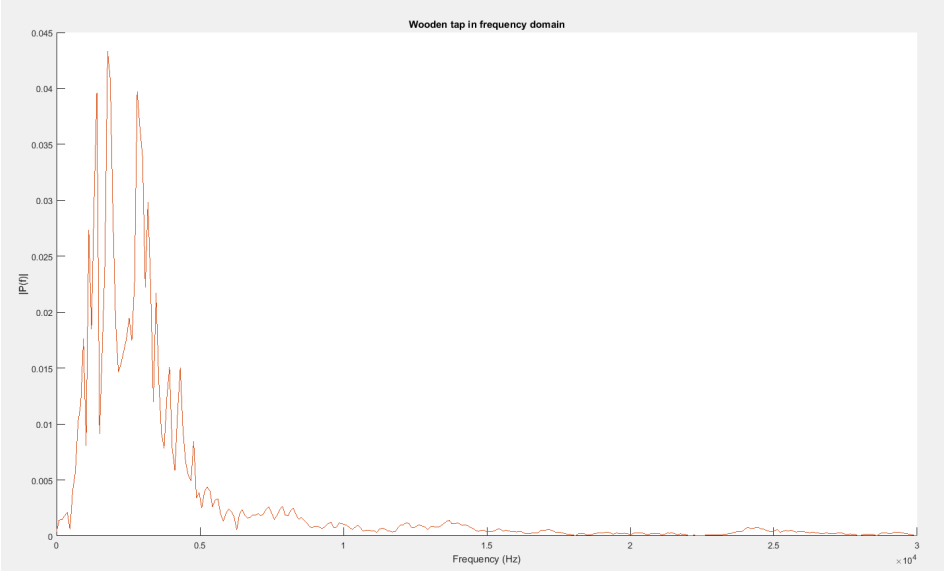

Figure 4.6: Power spectrum of a tap made by a wooden pen. The tap is the same shown in figure 4.3.

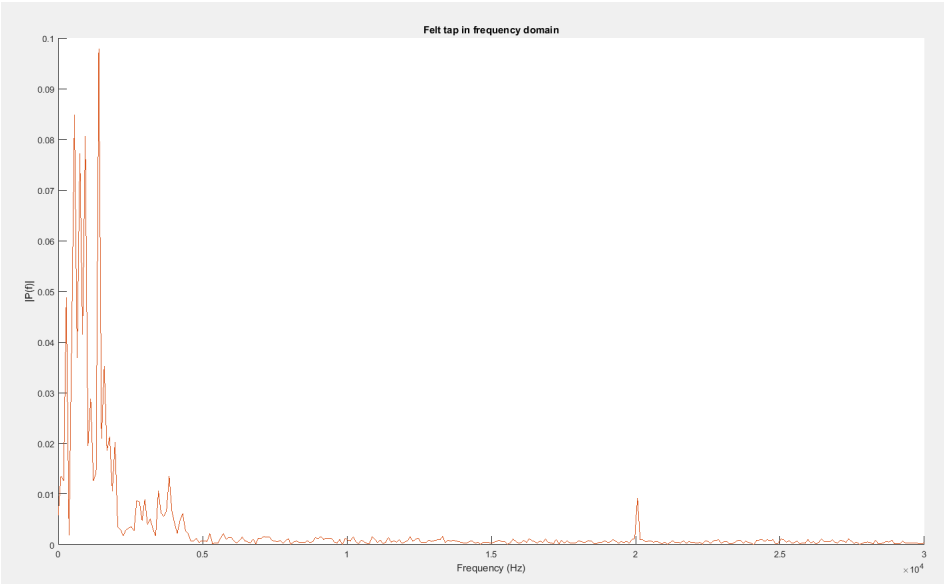

Figure 4.7: Power spectrum of a tap made by a felt pen. The tap is the same shown in figure 4.4.

To be able to easier compare touches of different force, all signals was normalized with respect to their total power. Even though the results showed that

the difference in force used for the impacts on the screen did not seem to follow a strictly linear behavior, the normalization was able to compensate for the force difference in most cases.

4.1.2 Sampling time

During the acquisition of the signals the frequency resolution was weighted against the signal to noise ratio, since longer sampling time means better frequency resolution, but it also means more noise because the material specific components will be attenuated and the amplitude of the signal lower as time passes by. From the time domain plot of the signals, see for instance 4.2, it appeared as if the material specific components was quickly attenuated, and choosing a long sampling time would thus dilute the signal with background noise, and noise in the form of the resonant frequencies of the glass and bezel.

To get some numbers for comparison between different sampling times, the power in the lower and upper frequency bands were calculated for the felt and metal pens for 0-6.5ms and from 6.5-13ms of sampling. The mean from 30 taps was calculated.

4.1.3 Classification

Since the materials that would be used were known, a material specific approach for the classification was chosen instead of a general. To find suitable features the signals for the different materials were plotted on top of each other to reveal in which areas the frequency spectrums for the different materials diverged from each other. Based on those plots it was seen which areas of the frequency spectrum that were the most different from each other, which would make the features used more effective and thus reduce the number of features needed. With a small number of features, overfitting is prevented, and more time can be spent on each feature to make them as significant as possible while the number of calculations for the algorithm is reduced. Based on those spectrum plots six features were chosen, referred to as feature 1-6. Each of those features describe a region of the frequency spectrum where there is a significant difference between the different materials. The features are shown in table 5.3

The KNN-algorithm used during this work is the KNN-classifier found in the MATLAB software, where K were set to 3. The Euclidean distance was used to determine the distance between points, and a weighted majority voting were used.

4.2 Experiment 1: Distance study

The first thing enquired was to find out whether the distance between the impacts on the screen and the vibration sensor affect how the signal received looks like. This was done by marking five different distances from the sensor while the force of the taps was kept in the same magnitude: 5cm, 50 cm 75cm 100cm and 140cm. Then 30 taps were made at each of those distances. The screen used in this study was the FF65", and the CM-01B sensor was used. The pens used for the impacts were the felt, wooden plastic and metal ones.

4.2.1 Frequency dependent acoustic attenuation study

To find out if the frequency dependent acoustic attenuation phenomena was apparent during the data collection a test was made where the power of the high frequency components was compared with the power in the lower frequencies of the signal, to see if any evidence of the higher frequency components being more attenuated than the low frequency components could be seen. The magnitude of the frequency dependent acoustic attenuation could be calculated if the theoretic material constants for the glass were known. However, after a long search no such material constants for the glass used or for any similar materials were found, and to find out the constants experimentally was not within the scope of this project.

The same data collected in the distance study was also used to do the test to see whether any effect of the frequency dependent acoustic attenuation could be noted, where the CM-01B contact microphone was used on the FF65" framed glass, and tape marked five different distances from the sensor while the force of the taps was kept in the same magnitude: 5cm, 50 cm 75cm 100cm and 140cm. At each of those distances, the glass was tapped 30 times with the wooden pen. The power in the higher frequency band of the sensing range (4000-5000Hz) was compared to the power in the lower frequency region (0-600Hz). If the higher frequencies would be attenuated more than the lower, the relation between power in the upper frequency band relative power in the lower band would drop off the further distance the sound would travel.

4.3 Experiment 2: Impact study

The next thing that was investigated was how different amplitude of the impact would change the signal when the same material was used at the same distance from the sensor. The small screen and the CM-01B sensor was used. The screen was tapped at the same distance from the screen, 10 cm, with 30 taps each of three different strengths of impacts with the felt, plastic and wooden pens.

4.4 Experiment 3: Screen size study

The third thing investigated was whether the signal would look the same if the same experimental set-up was used on a glass screen of larger size instead. A larger touch screen, the FF65" was used together with the smaller one, FF23". Both screens were tapped 5 cm away from the sensor with same force with the wooden, felt, metal and plastic pens. Unfortunately, the glass was not exactly the same for the two different screens. The FF65" glass had a different surface treatment and its frame was also different since it was fully built in with a metal case, while the FF23" was resting on a dampening layer of rubber.

4.5 Experiment 4: Pen angle study

The forth thing that was enquired was how much the angle of the pen affected the signal spectrum. The ACH-01 sensor was used on the small screen. The screen

was then tapped thirty times each with both a wooden and a plastic pen where the distance from the screen and force of the impact was kept as constant as possible by repeating the same motion while touching the screen. Three different angles of the pens were used. In 4.8 the angles used are shown, where the first figure shows a 90 degree angle, the second one a 45 degree angle and the third an angle of about 10 degrees.

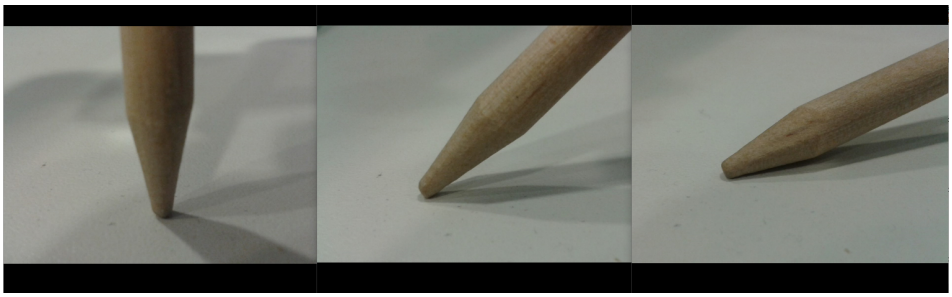

Figure 4.8: The different angles used during the experiment.

4.6 Experiment 5: Classification

4.6.1 Part one: One user

A data set of 360 data points was collected by the author to do a first study to find out if differentiation between the four different materials used, felt wood, plastic and metal could be done. All four materials had 90 taps each, and different distance from the sensor and different force were used to acquire the data. The data collected was picked up by the ACH-01 sensor, and the taps were made on the FF23" screen. 20% of the data was used as a test set and 80% of the data was used for training. A set of six features were used with the KNN-classification algorithm.

4.6.2 Part two: Multiple users

The last study was done to differentiate between the different materials in a case where the factors of impact, distance and angle were unknown to see if the different materials used could be correctly classified. A test was designed to capture normal writing and soft and hard touches made by a number of users. The ACH-01 sensor was used placed atop the FF23". A monitor was placed underneath the screen to show the test persons what they were supposed to write. The monitor showed a line and an amount of circles. On the line the users wrote a word with capital block letters and exclamation mark. The circles were of two different sizes. The larger sized circles were supposed to be tapped inside in a fast subsequence to result in harder taps. The smaller circles were supposed to be tapped inside carefully to get the user to tap more soft. The test was engineered to capture normal writing and also softer and harder touches, caused by the fine motion when writing in the small circles and the fast taps when writing in the larger circles.

This study reflect the differences caused by various users' way to write on the screen with objects, which covers force, angle, various locations on the screen and also things such as stiffness of the grip and wrist. Ten employees at FlatFrog participated in the data collection, where they wrote a word and tapped inside circles of the screen with different materials. At first five different users contributed with around 30 taps each for each different type of the materials: wood, plastic and metal. The felt pen was not used in this study due to the fact that only a small amount of the signals generated from the text writing could actually be recorded. In a study based on this data, all data from four of the users were used to train a KNN-classification algorithm while the last set of data was used for testing. After the data from the first five users had been evaluated, another five FlatFrog employees contributed with additional data. This time, the metal pen was not used since it was easy enough to classify correctly. Instead, the felt pen was used together with the plastic and wooden pens even though only some of the signals got recorded from the felt pen due to its low signal strength.

Chapter 5

Results

5.1 Preprocessing

5.1.1 Sampling time

The following values for the different sampling times was aquired. The values in table 5.1 is the mean from 30 taps. Since the metal pen is classified based on its high frequency components divided by the total power (frequencies > 7.5KHz), while the felt pen is mainly classified using the power in the lower frequency band divided by the total power as feature(0-0.6KHz), table 5.1 and **??** shows that both features for the felt and the metal pen becomes worse with the prolonged sampling time, since the felt should have a high value for feature one and a low for feature six, and the metal should have a low value for feature one and a high value for feature six.

Table 5.1: Comparison of feature 1 for different sampling times. The value is an indicator for the amount of power in the stated frequency band, where a higher number means higher energy.

Material	Sampling time	Value for feature 1(0-0.6KHz)
Felt	0-6.5ms	8.82
Felt	6.5-13ms	3.44
Metal	0-6.5ms	3.30
Metal	6.5-13ms	1.42

Table 5.2: Comparison of feature 6 for different sampling times. The value is an indicator for the amount of power in the stated frequency band, where a higher number means higher energy.

Material	Sampling time	Value for feature 6(7.5-16KHz)
Felt	0-6.5ms	1.18
Felt	6.5-13ms	4.59
Metal	0-6.5ms	11.91
Metal	6.5-13ms	10.67

5.2 Features

The following features shown in table 5.3 were the ones used during the experiments, chosen after analyzing the frequency spectrums for the different materials.

Table 5.3: Features used

Feature number	normalized power in frequency band
1	0-0.6KHz
2	0-2.5KHz
3	1.4-2.4KHz
4	2.4-3.7KHz
5	4-7KHz
6	7.5-16KHz

5.3 Experiment 1: Distance Study

When keeping the force of the impact constant and using the same object but at different distances from the sensor it was evident that the position of the impact relative to the sensor will matter. When measuring the power in different frequency bands, there was a notable difference in magnitude for some frequency bands for the same object, which can also be seen in figure 5.1.

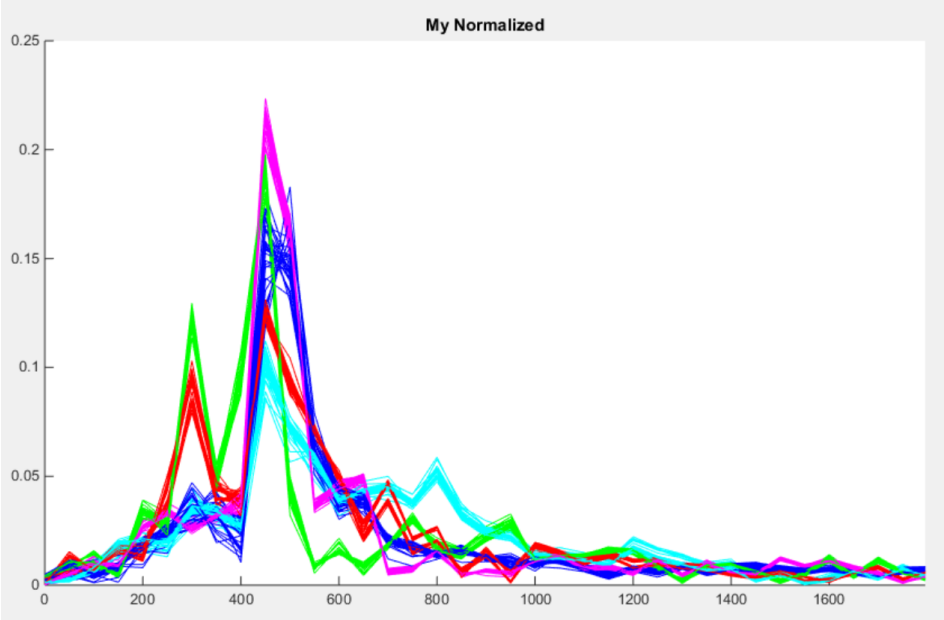

Figure 5.1: Each colour represents 30 touches made by the same material at different distances from the sensor.

In the figure 5.1, a wooden pen was used. Each colour represents 30 touches made by the same material at different distances from the sensor. The sensor placement was the same for each set of taps, and the force was kept within the same magnitude. Still, some frequencies seem to be enhanced at certain distances, which is believed to be caused by resonance frequencies for those distances.

5.3.1 Frequency dependent acoustic attenuation

A statistical t-test conducted to see weather any frequency dependent acoustic attenuation could be seen showed no significant result. The power of the higher frequency band was compared with the power in the lower band, and the hypothesis that the power measured at 140cm originates from a different distribution than the power at 5cm can be discarded.

Table 5.4: Power level for 4000-5000 Hz and 0-600 Hz at different distances. Taps made by wooden pen.

Distance from sensor	Power in the higher band divided by power in the lower band (mean from 30 taps) number in brackets variance.
5	0.071(2.587e-4)
50	0.076(4.174e-4)
75	0.040(4.205e-4)
100	0.047(1.444e-4)
140	0.066(7.440e-4)

5.4 Experiment 2: Impact study

From the impact study it became obvious that using different force would affect how the resulting signal would look like even after the signal had been normalized with respect to its total power. In the figure 5.2 the result of 90 taps of three different forces for the felt and wooden pen are shown, with 30 taps for each boxplot. Taps in the first boxplot are soft touches, moderate touches in the second one and hard touches in the third. The figure 5.2 shows the distribution in power for the frequency band 0-0.6KHz compared to the total power over all frequencies.

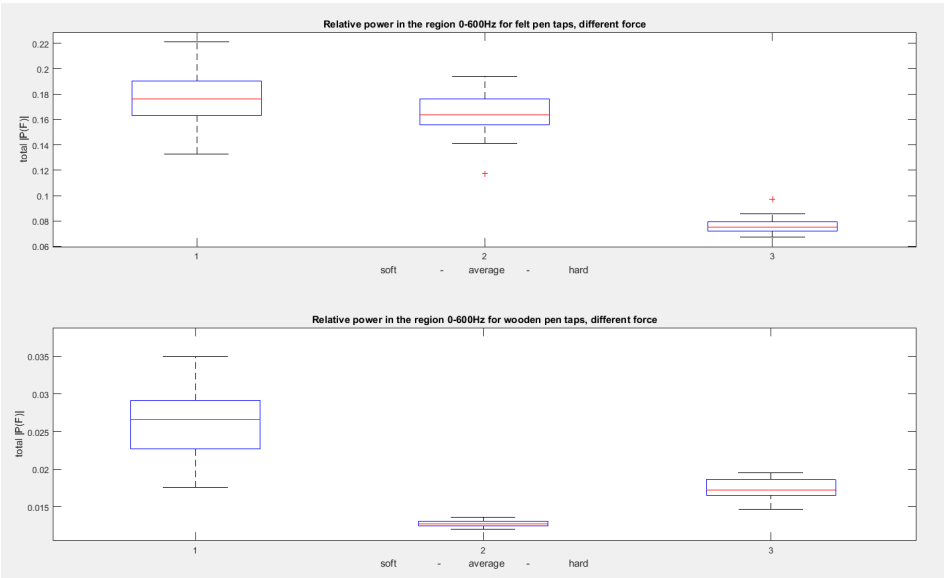

Figure 5.2: The top plot shows the distribution for different force used for the felt pen, and the bottom plot shows different force used for the wooden pen. Note that the scale on the y axis is different between the top and bottom figure.

5.5 Experiment 3: Screen size study

When the two screens, sized 23" and 65", were tapped and the signals recorded, where the force were kept in the same magnitude and the distance from the sensor was the same, 5 cm from the sensor, the following result was obtained: the time it took for the sound to dissipate on the FF65" screen for a mean of 30 taps compared to the time for the sound to dissipate on FF23" screen were 57% longer (the time it took to go below 50mV). The mean time to go below 50mV for taps on the FF23" at 1.8-2.2 V amplitude was 122 ms, while the mean time to go below 50mV for taps on the FF65" at 1.8-2.2 V amplitude was 191 ms. Figure 5.3 shows an example of a touch made on either of the two glass screens. From the figure it is seen that the time it takes for the signal to attenuate is longer on the larger sized screen.

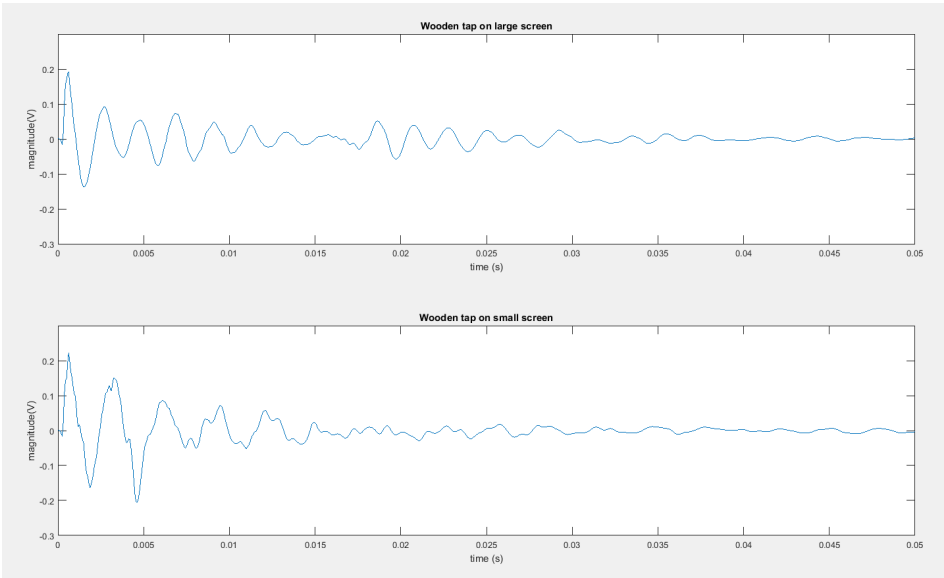

Figure 5.3: A touch with the wooden pen on the FF65" (top) compared to a touch on the FF23" screen(bottom).

5.6 Experiment 4: Pen angle study

During the data acquisition it appeared that the angle of the pen would matter with regard to how the frequency spectrum would look. To look into this matter data were recorded where the wooden pen was held in three different angles against the glass while tapping it, while the distance from the sensor and the force used were kept constant. The result showed that there were evident variations supposedly due to the different angle used. In figure 5.4 the result for the different angles for the wooden pen is shown, and in figure 5.5 the result for the various angles using the plastic pen. When looking at the figures, it is seen that for each material the signals have variations in frequency content. Still, the frequency plots are more similar to the other frequency plots for the same material but with different angles than the frequency plots of the other material.

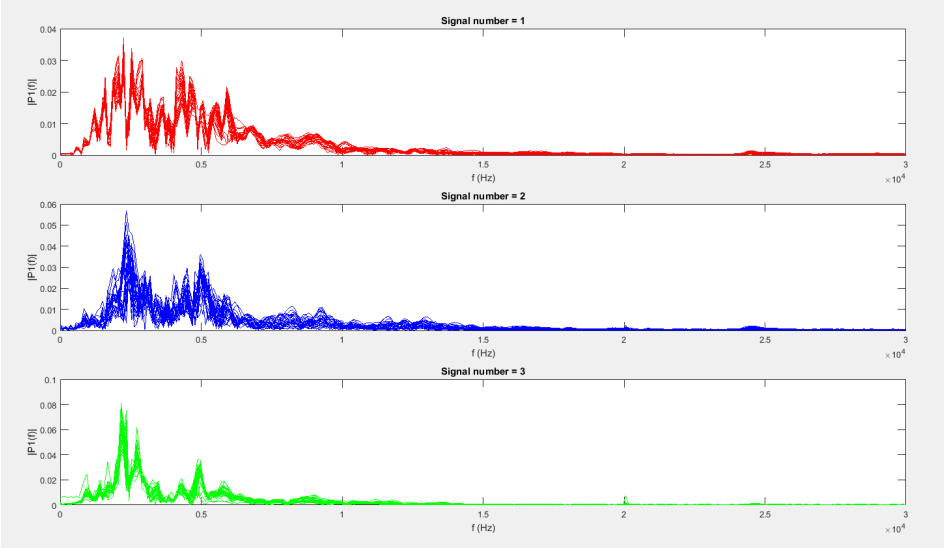

Figure 5.4: The figure shows three different cases where the wooden pen has been tapped on the screen 30 times with different angles, where the top plot is the angle 90 degrees, the middle with 45 degrees angle and the bottom one an angle of 10 degrees.

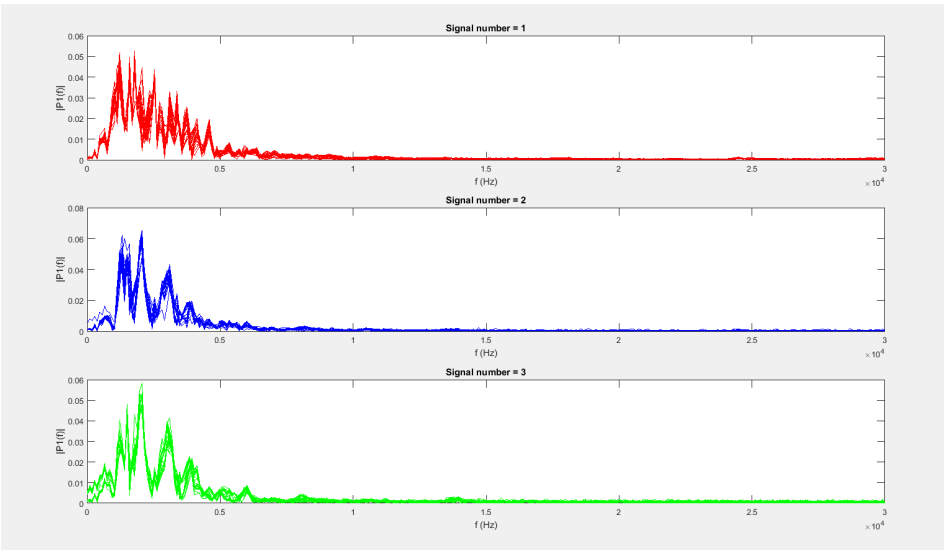

Figure 5.5: This figure shows 30 instances of touches made with the plastic pen made in three different angles, where the top plot is the angle 90 degrees, the middle with 45 degrees angle and the bottom one an angle of 10 degrees.

5.7 Experiment 5: Classification

One of the main goals with this project was to enquire how well sound signals made by different objects can be separated from each other. Figure 5.6 shows the frequency domain spectrum for the four main materials used in this study, felt, wood, plastic and metal.

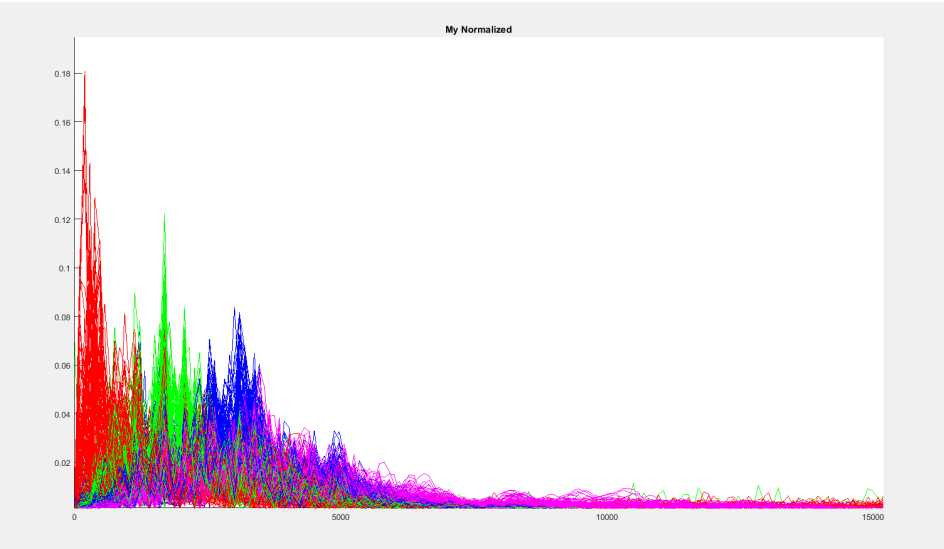

Figure 5.6: The figure above shows the frequency spectrum between 0-15KHz for the four materials, where the red plot represents the felt pen, the green represents the plastic the blue is wood and magenta is metal.

Figure 5.6 shows the frequency spectrum between 0-15KHz for the four materials, where the red plot represents the felt pen, the green represents the plastic the blue is wood and magenta is metal. Each color is made of 100 lines from taps from different users. Looking at this plot, it seems that the different colored spectrums could be possible to separate from each other. The two objects that are the hardest to discriminate from each other is the wooden and the plastic objects. In figure 5.7 the frequency plots for those two materials plotted on top of each other are shown.

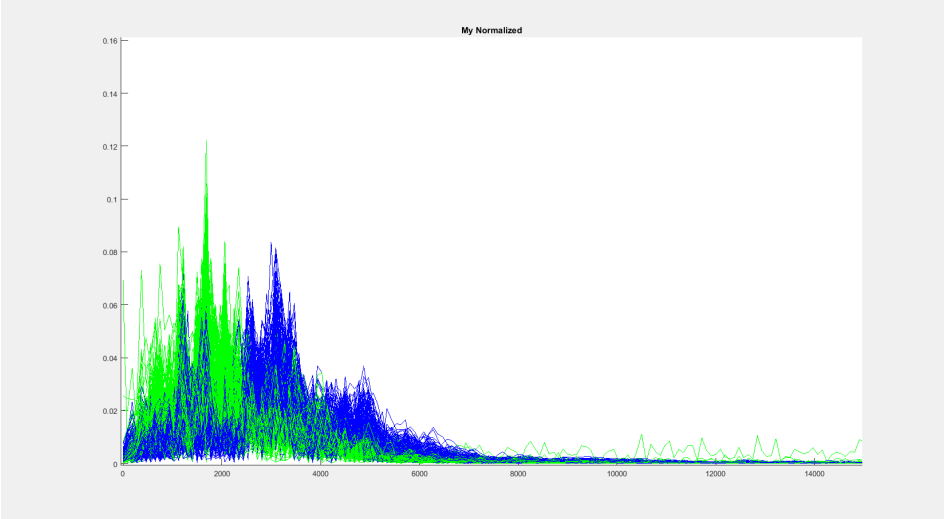

Figure 5.7: 160 taps each of plastic and wooden touches gathered from several users

Based on this frequency spectrum, seen in figure 5.7, three features are chosen to separate the distributions from each other, which are features number 2,3 and 4. Feature number two is the power of the frequency spectrum between 0 - 2,5KHz where the plastic(green) pen have a significantly higher level than the wooden. Feature number three and four were chosen as the power between 1,4-2,4KHz and the power between 2,4-3,7KHz, where the wooden material has a higher amount of power. In figures 5.9 b and c and figure 5.10 those three features are shown. As can be seen in the figures, the energy distributions between the wooden and plastic materials are mostly separated but with some overlap.

The combination of those three features manages to separate about 70% of the plastic and wood touches using only a simple threshold. The rest of those signals that were in the border region and might be wrongly classified were sorted out. In figure 5.8 the cases of wood and plastic pen taps that were harder to discriminate from each other is shown. Each color contains about 50 lines in the figure.

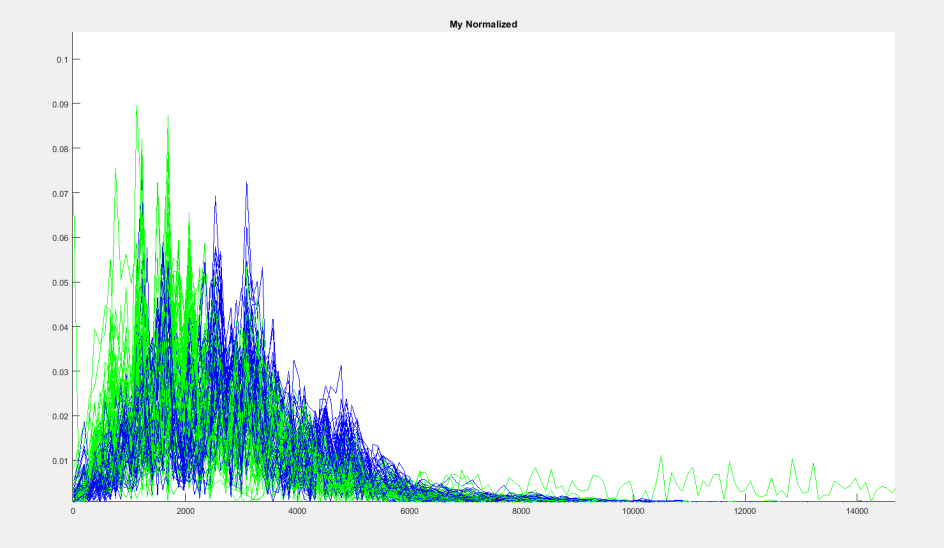

Figure 5.8: The instances of plastic and wooden pen touches that might be wrongfully classified due to their overlapping feature vectors.

Figure 5.8 shows the instances of plastic and wooden pen touches that might be wrongfully classified do to their overlapping feature vectors. The fact that the feature vectors overlap in this region does not however mean that all those taps will be wrongfully classified, but it means that there is a risk that they will be. In fact, most of those taps (around 70%) will be correctly classified due to being closer to their own class, using the same KNN-classifier as described in section 4.1.3 with the three features stated above (feature 2,3 and 4).

When the feature vectors had been updated to better sort out the wooden and plastic pen touches from each other, the following feature distributions was obtained for the taps from the data of all ten test persons. In figure 5.9 the feature distribution for the first to the third feature are shown, while figure 5.10 shows features four to six. In figure 5.9 C we can see that this feature seems to do a good job to single out the plastic pen, while the first feature in A is good at the felt pen and also the metal one. The feature that does the best job at classifying the wooden pen is seen in figure 5.10 A. No feature seems to be good enough to sort out the materials alone, but using them all in combination the result will be quite good.

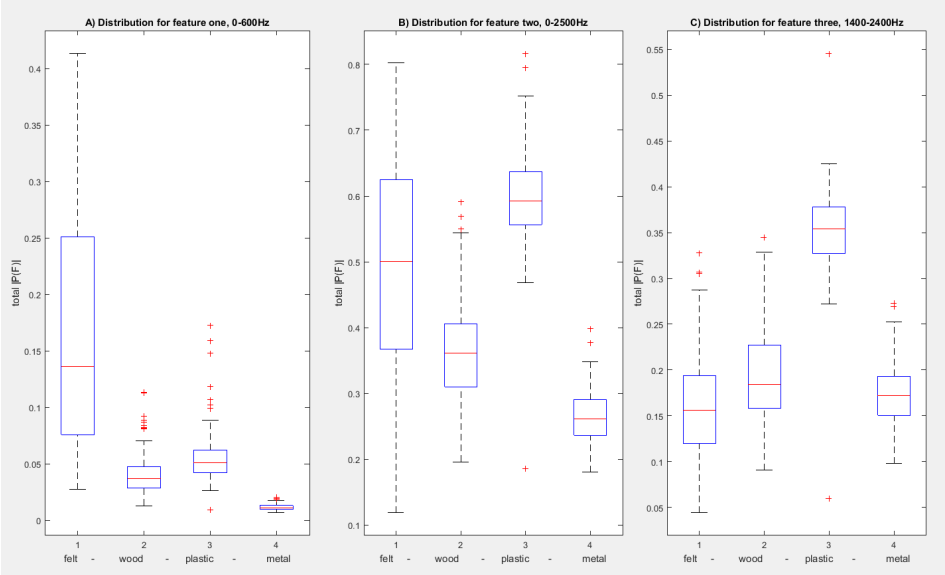

Figure 5.9: Distributions for feature number 1-3 for the different materials

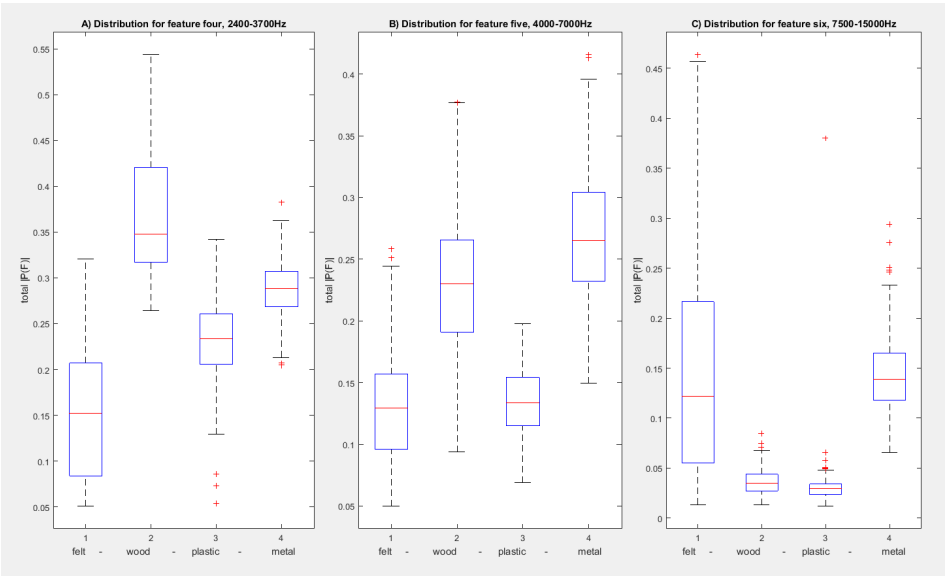

Figure 5.10: Distributions for feature number 4-6 for the different materials

5.7.1 Part one: One user

A data set of 360 data points all collected by the author was used as a first study to find out if differentiation between the four different materials used, felt wood, plastic and metal could be done. All four materials had 90 taps each, and different distance from the sensor and different force had been used to acquire the data. Using a set of six feature vectors and the KNN classification, a correct hit rate of about 99% was achieved , using the same KNN-classifier as described in section 4.1.3.

5.7.2 Part two: Multiple users

From the first five users' data where the three objects metal, wood and plastic was used the KNN-algorithm was trained with four of the users' data while the fifth data set was used for testing. This was done so that each persons data were used as test set once. The correct classification rate ended up at around 95%, (ranging from 90-98%).

After the additional data collection where five new persons contributed with data, and where the felt pen was used instead of the metal pen, the KNN- algorithm was trained again using the data from nine users while the last data set was used for testing. The four object classification had a mean of 92% when each users data had been used for testing once. If the object with the worst correct classification amount was removed, which was wood since its features laid in between the plastic and metal objects, the correct classification increased to 96%. Between two objects, either felt and metal or plastic and metal a correct classification above 99.5% was achieved.

Chapter 6
Discussion

Previous works have used quite much longer sampling time than I did during my experiments. In most cases the reason stated if any is to receive a higher number of frequency bands to increase the spectral resolution. The Tapsense study mentions that since the features are time-independent they could potentially use only a quarter or less of the 43ms they used during their study [4]. While it is true that the frequency resolution is increased with a prolonged sampling time, I thought that the reduction in signal quality was worse than a reduction in spectral resolution. A shorter sampling time will also allow a shorted delay between the touch and the detection of the event in a potential system using this technique.

When the different distances from the sensor was tested it was noted that for some distances, some frequencies were enhanced. This is believed to be caused by the fact that the soundwaves in the glass will have different nodes and antinodes in the glass, and at certain distances away from the sensor some frequencies will have a higher or lower amplitude. This means that care must be taken when creating feature vectors, since the feature must not be based on an amplitude that is strong for only one certain distance. To avoid this, the feature vectors were created based on data collected from several different users, where the distance from the sensor varied. The result of the frequency dependent attenuation test showed that no significant difference could be noted between the power in the higher and lower frequency bands. This does not mean that the frequency dependent acoustic attenuation is not present, it might just be too small to be detected due to the distance travelled is small, that the difference in frequency is small or because of a poor experimental setup. Ideally, a setup where the screen could be tapped with equal force should have been used, which would also have made it possible to find theoretic values for the frequency dependent acoustic attenuation material constants for the glass.

The second experiment was conducted to investigate if any differences could be seen in the frequency spectrum of the signal if the glass pane was tapped at the same distance from the sensor and with the same type of material but with alternating power. The a priori assumption is that only the amplitude will have changed, and that it is changed equally for all frequencies. This would prove very useful, since it would mean that a difference in force used would follow a linear behaviour and could easily be normalized. However, the study of the matter showed that this did not seem to be the case. Instead, the distribution of the

power in the frequency spectrum seems to be dependent on the force used when the object touches the screen. A normalisation of the frequency spectrum did still improve the result, but perhaps the normalisation should be done as a function of the amplitude of the signal. The reason for this non-linear behaviour is yet unknown, but possibilities include signal contribution from new materials in the casing, i.e. the metal case could start resonate if the glass is stroked to hard, or it could be dependant on the contact time. It might also be that some components are still present in the glass, not fully attenuated before the next strike and the next strike will thus have an addition of frequency components of the frequencies that take the longest time to completely dissipate. I might also be that the sensor would miss high energy low frequency components, or that the noise composed of all frequencies is increased when the glass begins vibrating to violently. It appeared that some sort of threshold value is present, since there is a sudden drastic change when the power of the strike goes high enough. This suggests that there are vibrations from new components in the glass if the screen is stroked hard enough, for instance the bezel could be resonating. To conduct a more accurate test some sort of specifiable instrument that can tap the screen with a desired force would be needed, since all studies was done tapping the screen by hand which introduces larger error margins.

When using the two differently sized screens the results showed that the time for the signal to dissipate is longer for a larger object, which is also mentioned in the Tapsense paper, that a larger surface will take longer time to dampen out the sound resulting from the impact. If the screen is to large, the microphone will have problems to pick up the sound originating from the source far away from the microphone since the energy will dissipate as the sound propagates through the surface. This means that an acoustic sensing system benefits from a small size, both because of the attenuation of the signal caused by the sound travelling a further distance and also because previous sounds are dampened faster in a small system.

It became apparent that the angle of the pen played a major role in weather the pen would be correctly classified or not for the objects with pointy tips. The pens used does simply not make the same sound for different angles between the tip of the pen and the screen. If the tip of the pen would be more spherically shaped, I believe that the variance between the different impacts on the screen with the pen is less pronounced or not present at all.

The classification of different materials for different users were quite good. For exactly two objects, a complete discrimination could be achieved. When three different materials were used the correct classification were around 96%, and when four materials were used the correct classification was around 92%. The experiment was meant to classify unknown taps, but since the test was constructed to capture normal handwriting and soft and hard touches, all users probably used approximately the same angle and force when writing which means that the taps were not completely random. With improvements to this sensing system, I believe that it would be possible to increase the correct classification rate, maybe up to four-five objects completely separated by their different acoustic signature. The sensor could be better adhered to the screen, and a larger number of sensors could be used.

The metal object would most probably not be able to be used in a real solution since the noise it makes is unpleasant, but since its frequency components are very high the metal object is easy to classify. The felt pen is also quite easy to classify since all its frequency components are in the lower band. There is however a couple of problems connected with the felt pen. The main problem is that since the pen is so soft, the sound signal it creates from the impact with the screen is low which means that soft impacts made with the felt pen is impossible to classify since they do not go above the noise level. This also means that felt pen taps of moderate force but far from the sensor is also impossible to pick up since all the sound dissipates in the glass. Another problem connected with the felt pen is that when a signal is picked up, its signal to noise ratio is quite low, which can be seen in the figures 5.9 and 5.10, where we can see that the variance for the felt pen is quite large in every plot. This means that the signal recorded contains noise with frequencies in the whole spectrum, and since only the metal pen has frequency components in the higher frequency spectrum the felt pen is sometimes misclassified as being metal. Those felt taps that wrongfully gets misclassified as metal should instead be disregarded due to their low signal strength. Finding suitable materials to use on the touch screen in a realistic implementation is not the easiest task. There are several factors to include such as user friendliness in terms of how the material feel and sounds like. If the material makes an unpleasant sound, is uncomfortable to hold or leaves marks on the screen they are not possible to use. The different materials must also sound significantly different from each other to make a good discrimination based on the acoustic pattern possible.

The contact microphone is excellent at not picking up sound mediated through the air. All the signals of significant amplitude that are picked up originates from vibrations in the screen, and a noisy environment around the monitor is thus not a problem. Still there are some noise in form of vibrations in the glass that does not originate from taps on the screen. This might be someone that touches the frame of the screen or the floor or wall where the screen is located. Vibrations that are introduced in this way will be picked up by the sensor, but if the systems optical sensors do not detect a touch then any such noise can be ignored and will only cause a problem if they occur at the same time as actual taps on the screen. There is a constant noise level present while the sensor is active which makes touches that are too soft impossible to detect. This noise also makes the soft touches harder to correctly classify since the signal to noise ratio goes down the weaker the signal is, and the noise present in the signal contains every frequency.

The time it takes from the tap on the screen until the result of the resulting sound signal is processed is mainly dependent on three factors: the time it takes for the sound to reach the sensor, the time during which the signal is sampled and thirdly the time it takes for the computer to execute the calculations. Since the sound of the speed in glass is 4km/s and the furthest distance travelled in the glass for the larger screen is 140 cm this factor gives a very small delay, less than 0,1ms. The sampling time used was around 6ms, and the computational time was also short, within a few milliseconds which makes the system possible to be implemented in real time.

To get as good samples of the signal as possible, it is important that the sensor is thoroughly adhered to the surface, if it does not have good enough contact with the screen the signals received will be noisier, and more force is also required to give a sensor reading if the sensor is not properly fastened against the surface. Signals made with significant force are also easier to correctly classify since their signal to noise ratio is higher.

Differentiation of different kind of materials based on their acoustic signature made from the impact with a surface have great potential in my opinion. During my study a high correct classification percent was achieved for three different kind of materials. Given more time developing the algorithm and creating objects engineered for this purpose this correct classification amount will certainly be increased.

The acoustic sensing system would perhaps not be ultimately implemented in the multi-touch devices on which the study was conducted, at least not on the FF65" since the distance between the sensor and the touches could be quite long. Another problem is that two events happening at the exact same time will be superimposed, which makes simultaneous events hard to correctly classify. Events that is happening with about 10ms time between them can be detected as individual events so this might not cause to much trouble event if the screen is intended for multi-touch use.

With the acoustic sensor attached to the screen, not only would it be possible to discriminate between different types of materials that touch the screen, but it could also prove helpful in other ways. A couple of the problems with the touch system today could potentially be solved. The first thing to note is taps made in rapid succession or when only lifting the object touching the screen slightly, which can be when the dots over letters are written. Those touches will not always be discriminated as two independent touch events but perhaps rather as a drag, and thus a lower case 'i' will be seen as an 'I' instead. The acoustic sensor however can notice two events as individual if they happen with more than 10ms time between them, which is much less than the time for a double tap. Another problem with a touch screen that is not capacitive might be that unwanted objects that touch the screen, such as palms of the hand will produce true events that is still unwanted. The palms of the hand when a pen is used is a common problem among touch screen developing companies. In this case, the acoustic sensor could be useful to help sort out which material the different touches are made of, and thus can aid the system in rejecting unwanted touches by adding additional information as long as the vibration from the palm is strong enough to be picked up by the acoustic sensor. If the sound it makes is to low a tap detected by the touch system but not the acoustic sensor could possibly be rejected as unwanted.
The technology with object differentiation based on the acoustic signals that arrives from a materials impact with some surface could be a useful tool in several aspects, as an inexpensive way to make a surface interactive. This sort of technology is also well placed in this current computer age with the growth of internet of things and easy accessible sensors and computer to process the data. As an example, Windows latest OS Windows 10 is made to be user-friendly on touch

devices and also supports multi-touch inputs. The passive pen approach based on the acoustic sensors is superior to the active pen approach in several ways. One of the upsides is that the passive pens are much cheaper to produce and they can be made out of simple environmental friendly materials such as wood and felt, instead of the alternative with the active pens with electronic components. An active pen also always need power, and might also interfere with other electric equipment with frequency disruption and such.

6.1 Future work

I believe that there is a large potential in improving the classification algorithm to achieve a higher correct classification rate. More data could be collected to train the classifier, a larger set of features could be used including features of higher order and weighted features. Since both force, distance and angle of the touches should be taken into account, the data used for training should cover all those aspects. I also believe that better objects could be produced for the purpose of being used on a touch screen while they are engineered to have their own characteristic acoustic signatures. Another thing that could be improved is the sensor placement, since it is suboptimal to have it taped to the screen, and perhaps also use more than one sensor.

It would also be interesting to look at classification done with a decision tree, since it would be able to quickly sort out the easily classified metal object and it would be interesting to see if the decision tree would perform better than the KNN-algorithm.

All the resulting features used were based on the materials spectral components. Other works have used amplitude in addition with the spectral component features. An amplitude feature was tested but since it could not discriminate between a close touch of a soft object or a distant touch made by a higher density object the amplitude feature was abandoned. If it could be combined with a distance measurement however, using for instance the optical detection system to give distance input, I believe that the amplitude feature could be quite useful. A duration feature was considered to use the attenuation time as feature, but since it would increase the sampling time drastically, and also because it is correlated with the amplitude of the signal (low amplitude signals take longer time to attenuate) it was never tried. With more time however, a larger number of different types of features would be interesting to study.

Some of the problems encountered during the experiments were that new factors that affected the signal was discovered gradually during the experiments. If the experiments that were conducted during this work would have been known from the beginning, a more accurate experimental set-up could have been used with some machine that could use a desired force each time instead of taps made by hand with only approximately the same force.

An acoustic sensing system as the one used in this paper could also improve the amount of false positives of the optical touch system. The information from the acoustic sensor in addition to the optical system could potentially reject "ghost touches" if there is no coincidence between the information from the acoustic sensor

and the optical sensor, given that the acoustic sensor is sensitive enough.

6.2 Conclusions

The report shows that differentiation of objects by means of acoustic sensing has potential to reach a state where it can be used in a real product. The differentiation is done based on the unique acoustic signature different materials produce when striking a surface. The differentiation between two objects could be done with an accuracy of over 99.5%. The differentiation for three objects were 96% and with four objects 92%.

The report also shows that it is important to take into account several different aspects such as angle, force and distance from the sensor into account if such a sensing system is to be realized in a real product.

The report points out that the sensing system would benefit from a small size of the screen the objects will touch, and also from using pens without a pointy tip, which might be two big obstacles for realizing this in a real product of the larger touch screens FlatFrog is developing.

The project also shows that soft materials, such as the felt pen or a finger, are hard to use because of their low signal strength. Even if their acoustic signature could easily be identified, the signal they produce will dissipate before it reaches the sensor.

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