Computational analysis of style in Irish traditional flute playing

Islah Ali-MacLachlan

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Abstract

The wooden flute is a common melodic instrument used in Irish traditional music (ITM). A player's style is a personal interpretation of a traditional melody reflecting technical skill, education, heritage and influences. Mastery of the instrument is reflected in the ability to individualise a tune in real-time using ornamentation, dynamics, phrasing and changes in timbre.

The aim of this thesis is to develop automated analysis tools for stylistic traits in ITM flute performances. This is achieved through specialised computational methods capable of note onset detection, ornament detection and player recognition. Parameterisation of these tools is informed by ethnomusicological research into how ITM is made on the flute. This discussion covers the instrument, its operation and history and an overview of the ITM timeline. The use of computational analysis in the definition of stylistic differences between players is intended to offer objective measurements for ethnomusicology research and provide educative value for practitioners.

To train the proposed systems, two corpora have been created. The first is comprised of released recordings with 18,000 annotated events including pitch, timing and note type information. The second dataset was specifically recorded to allow comparative studies in a more controlled manner. It is comprised of recordings of timed and untimed versions of the same set of popular tunes as performed by six professional players. Using these datasets, four evaluations were conducted to determine the performance of the proposed systems. The proposed note onset detection system results in an F-measure of 88.5, which is higher than current state of the art systems. The ornament detection system achieves a mean accuracy of 84% across a range of contexts, outperforming leading generalised systems. The player recognition system is capable of identifying a single player with an accuracy of 90%. This demonstrates the worth of the proposed systems, highlighting the importance of style-specific training of models and confirming the need for historical and musicological domain knowledge.

Acknowledgements

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Several musicians have made precious time or facilities available, allowing me to record the datasets used in this thesis. I would like to express my heartfelt thanks to: Dot Brodie, Oisín Cooke, Bryan Duggan, Jem Hammond, Vince Jordan, Noel Lenihan, Mark McCabe, Mark Priestley, Michael Walsh and Bev Whelan–sláinte mhath.

In 2017, folk music lost a shining star. From the bottom of my heart I would like to thank Alan Surtees for friendship, inspiration and energy. Your passion in providing a stage for traditional music will live on in countless others. Learn it, love it, pass it on!

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Chapter 1

Introduction

> *Folk music is a heritage which is passed on from one age to the next–hence the term 'traditional' which is usually applied to it in Ireland. Irish folk music includes not only the older songs and melodies of the Gael, which are undoubtedly our most precious heritage, but also the Anglo-Irish and English ballads of the countryside and the extraordinarily rich vein of dance music which belongs exclusively neither to Gaeltacht*[1] *or Galltacht*[2] (Breathnach, 1996)

Irish traditional music (ITM) is central to the culture of the Irish people, having evolved as part of the rich history of the country. The flute is one of several instruments that has a long association with the dance music of Ireland alongside the fiddle (violin), tin whistle and bagpipes. In ITM, traditional melodies are interpreted by the player who uses personal judgment and skill to create music that reflects their mastery on the instrument as well as providing clues as to their geographical roots, education and influences. The melody is a framework and personal stylistic traits such as ornamentation, dynamics and changes in timbre are added in real-time (Breathnach, 1996; Carson, 1997).

Discussions concerning style in Irish traditional music are often constrained by inadequate language, leading to a lack of clarity in description and analysis of the music (Keegan, 1997; Keegan, 2011). Ornaments are not usually noted in transcriptions, including those by the celebrated Irish scholar Breandán Breathnach (1963; 1976; 1985), who recognised the limitations in notating collected music in this way.

Computational analysis of stylistic difference in ITM would inform debate between ethnomusicologists and practitioners, allowing for variances in playing style to be analysed in terms of regional styles

[1] Gaelic-speaking area
[2] English-speaking area

or changes in tradition (Köküer et al., 2017).

The main aim of this thesis is to determine methods for the analysis of these stylistic features. However, to appreciate the relevance of stylistic features it is important to understand the music, its history and cultural identity, and the instrument along with its performance and interaction with the player. In order to understand ITM and its relationship with the flute, a systematic ethnographic study has been undertaken so that the importance and frequency of stylistic features can be studied. This will allow for a greater understanding of the cultural data embedded in ITM and enable research questions to be answered by building relevant and useful models.

1.1 Background and motivation

ITM is played and listened to in Ireland as well as many countries round the world where Irish communities have settled and evolved. The origins of the Irish diaspora are part of a political and social history that is as much an ingredient of the evolution of the music as the development of regional playing styles or the transfer of ornamentation from one instrument to another.

The conical-bored simple system wooden flute came to prominence in ITM the 1800s but it had already been used in European music for several hundred years. The cylindrical wooden instrument of the Renaissance period in the 1500s evolved into the conical-bored Baroque flute of the 1600s. The requirement of the instrument to play a wider range of chromatic notes led to the development of metal keys capable of sounding a wider range of pitches. The use of ornamentation around this time also individualised the playing style of musicians.

By the 1600s, there is documentary evidence that dancing was widespread in Ireland, as a social pastime and means to celebrate (Brennan, 2001). The music that accompanied this dancing evolved over several hundred years from being played by solo pipers and fiddle players in house parties to céili bands with twenty or more members playing at large, public gatherings. The music now also has new audiences, featuring in concerts as well as musical gatherings, or seisúns in pubs or other communal areas.

The history and social context of Irish music has been written by cultural historians and ethnomusicologists such as McCullough (1977), Ó Canainn (1978), Ó Riada (1982), Breathnach (1996), Williams (2010), and Vallely (2011). The relationship between the flute, or the closely-related tin whistle, and ITM have also been documented in many books including Vallely (1986), McCullough (1987), Hamilton (1990) and Larsen (2003).

Exploration into timbral differences between classical flute players has been explored by Widholm et al. (2001) and analysis of traditional Irish flute and tin whistle playing has been undertaken by a team from Dublin Instiute of Technology (DIT) including Gainza et al. (2004a), Gainza et al. (2004b), Kelleher (2005) and Duggan et al. (2006).

Although the stylistic implications of ITM has been discussed in Keegan (2010) and its relationship with regional styles in Keegan (1997) and Kearney (2012), very little work has concentrated on quantifying the stylistic differences between individual flute players.

Flute players can individualise their playing styles in a number of ways using timbral and temporal methods. Timbre can be changed by adjusting the shape of the mouth and air column as part of the embouchure, along with the strength of breath. Temporally, the use of various notes and ornaments alongside breaths and dynamics can be employed as a way to classify individual players.

The use of computational analysis is important in defining these differences. Providing a taxonomy of timbral and temporal attributes can assist in understanding differences and similarities between players. Analysis of this type is useful in player identification and to quantify the use of individual stylistic features. This type of assessment will allow ethnomusicologists to more clearly understand relationships between regional styles and individual players as well as evolution of playing over time. It will also be useful in the development of teaching tools that will allow learners to develop good playing tone alongside ornamentation in context.

1.2 Aim and objectives

The overarching aim of this thesis is to produce methods for the recognition and analysis of stylistic traits in Irish traditional flute playing.

The objectives are:

- To develop computational methods for automatic analysis of stylistic differences between traditional flute players in order to provide a deeper understanding of timbral and temporal components.

- To provide a corpus of recordings with relevant metadata for the analysis of stylistic differences between traditional flute players.

- To provide an explanation of how Irish traditional music is made on the concert flute. This discussion covers the instrument, its history and its operation along with a history of Irish traditional music from the perspective of the concert flute, detailing the major movements associated with both timelines. This information has not yet been captured in a singular document.

1.3 Contributions

- The development of a set of analysis methods for defining stylistic differences between Irish traditional flute players: Preliminary study with three players of differing levels showing that players contribute more towards overall timbre than individual instruments (Ali-MacLachlan et al., 2013). A method of player identification using magnitudes of partials derived from individual notes (Ali-MacLachlan et al., 2015). Development of a method for player identification using machine learning based on segments of recordings output as compact timbral features. (Ali-MacLachlan et al., 2018).

- The *ITM-Flute-99* dataset comprising of 99 solo flute tunes played by 10 professional players. The metadata comprises over 15,000 individual notes with ground truth annotation (Köküer et al., 2014b; Köküer et al., 2017). The *ITM-Flute-Style6* dataset containing 168 recordings of 6 players. This includes all musicians playing the same melodies at the same tempo.

- A new annotation methodology including: A novel method of producing ground truth pitch and timing metadata for solo instrumental melodies (Köküer et al., 2014b; Köküer et al., 2017); and a method for error checking of manual annotation by using an onset detector and window of acceptance comparison method (Ali-MacLachlan et al., 2017).

- An appraisal of high-performing onset detection algorithms used on flute signals (Ali-MacLachlan et al., 2016). Development of training data for a machine learning algorithm that outperforms current state of the art onset detectors on solo traditional flute recordings (Ali-MacLachlan et al., 2017).

1.4 Published papers

Ali-MacLachlan, Islah, Münevver Köküer, Peter Jancovic, Ian Williams, and Cham Athwal. 2013. Quantifying Timbral Variations in Traditional Irish Flute Playing. In *Proceedings of the 3rd International Workshop on Folk Music Analysis.* Amsterdam, Netherlands.

Köküer, Münevver, Peter Jancovic, Islah Ali-MacLachlan, and Cham Athwal. 2014. Automated Detection of Single-and Multi-Note Ornaments in Irish Traditional Flute Playing. In *Proceedings of the 15th International Society for Music Information Retrieval Conference (ISMIR),* Taipei, Taiwan.

Kökϋer, Münevver, Islah Ali-MacLachlan, Peter Jancovic, and Cham Athwal. 2014. Automated Detection of Single-Note Ornaments in Irish Traditional Flute Playing. In *Proceedings of the 4th International Workshop on Folk Music Analysis.* Istanbul, Turkey.

Köküer, Münevver, Daithi Kearney, Islah Ali-MacLachlan, Peter Jancovic, and Cham Athwal. 2014. Towards the Creation of Digital Library Content to Study Aspects of Style in Irish Traditional Music. In *Proceedings of the 1st International Workshop on Digital Libraries for Musicology.* London, UK.

Ali-MacLachlan, Islah, Münevver Köküer, Cham Athwal, and Peter Jancovic. 2015. Towards the Identification of Irish Traditional Flute Players from Commercial Recordings. In *Proceedings of the 5th International Workshop on Folk Music Analysis.* Paris, France.

Ali-MacLachlan, Islah, Maciej Tomczak, Carl Southall, and Jason Hockman. 2016. Note, Cut and Strike Detection for Traditional Irish Flute Recordings. In *Proceedings of the 6th International Workshop on Folk Music Analysis.* Dublin, Ireland.

Ali-MacLachlan, Islah, Carl Southall, Maciej Tomczak, and Jason Hockman. 2017. Improved Onset Detection for Traditional Irish Flute Recordings Using Convolutional Neural Networks. In *Proceedings of the 7th International Workshop on Folk Music Analysis.* Malaga, Spain.

Ali-MacLachlan, Islah, Carl Southall, Maciej Tomczak, and Jason Hockman. 2018. Player Recognition for Traditional Irish Flute Recordings. In *Proceedings of the 8th International Workshop on Folk Music Analysis. Thessaloniki, Greece.*

Köküer, Münevver, Islah Ali-MacLachlan, Daithi Kearney, and Peter Jancovic. 2019. Curating and Annotating a Collection of Traditional Irish Recordings to Facilitate Stylistic Analysis. *Special Issue of the International Journal of Digital Libraries (IJDL) on Digital Libraries for Musicology.*

1.5 Chapter overview

The remainder of this thesis is presented as four main chapters: The history, design and operation of the concert flute in the context of Irish traditional music (Chapter 2); data sets collected and used in studies (Chapter 3); a literature review of technologies used in the analysis of flute playing (Chapter 4); a description of methods used in the identification of timbral and temporal features (Chapter 5). Conclusions are presented in Chapter 6.

Chapter 2 consists of five sections: Section 2.1 introduces the flute used in the playing of ITM. Section 2.2 discusses the types of melodies played in ITM along with their origins. Section 2.3 documents the development and evolution of the modern concert flute; Section 2.4 explains how the flute produces sound and Section 2.5 discusses stylistic features and types of ornamentation. Section 2.6 contains a chapter summary.

Chapter 3 consists of two sections: Section 3.2 describes the *ITM-Flute-99* dataset and Section 3.3 describes the *ITM-Flute-Style6* dataset. Section 3.4 contains a chapter summary.

Chapter 4 consists of three sections: Section 4.1 considers the technologies used to analyse audio in order to quantify timbre. Section 4.2 considers the technologies used to automatically identify event onsets and in Section 4.3, flute-specific methods are discussed. Section 4.4 contains a chapter summary.

Chapter 5 consists of five studies in identification of timbral and temporal features: Section 5.1 presents a study quantifying the timbral differences between a range of concert flutes and a number of flute players. Section 5.2 presents a player identification method using recordings contained in the *ITM-Flute-99* dataset. Section 5.3 presents a method for detecting notes and single-note ornaments using a feed-forward neural network in comparison with eleven leading onset detection methods. Events were analysed in context by considering the signal elements directly before and after. Section 5.4 presents an onset detection method using convolutional neural networks in order to further examine notes and ornaments in context. An examination into the effectiveness of training neural networks with specific data in comparison to generalised data was also performed. Section 5.5 presents a player identification method using recordings from both *ITM-Flute-99* and *ITM-Flute-Style6* datasets and finally, Section 5.6 contains a chapter summary.

Chapter 6 presents the conclusions of the dissertation in three sections: Section 6.1 provides a summary of the dissertation; Section 6.2 reiterates the contributions of this thesis; and Section 6.3 outlines possible directions for future research in this area.

Chapter 2

Creating Irish traditional music on the flute

Irish traditional music (ITM) has developed through historical, social and musical change. Folk music is a living tradition and as such it is nurtured and advanced by generations. The study of stylistic features within traditional music requires an understanding of the evolution of the music and the context in which it has developed. It also requires a detailed understanding of the instrument and its acoustical properties. In order to develop this understanding, this thesis explores a number of important issues that are related to the playing of ITM on the flute.

This chapter explores the historical and social context of the Irish people and their music from its Celtic roots, through famine, emigration, decline, and revival to a modern day tradition that is vibrant and popular. Traditional music and dance are often closely related and the evolution of folk dances are discussed in this context. The central instrument of this study, the blackwood or concert flute, is discussed along with related melody-playing instruments in the tradition, showing how the instrument and its playing style has evolved and integrated with the tradition. A detailed history of the concert flute is presented in Section 2.3.

ITM is part of a wider system of traditional music that encompasses Scotland, Scandinavia and other European countries. Each country has developed this music individually through a process of reworking, with differences in politics and geography adding to the mix of culture and traditions (Ó Súilleabháin, 1981). Within Ireland there are also regional styles that evolved out of popularity of particular instruments and influence of key musicians as well as the aforementioned political and geographical factors.

The music is inextricably linked to dancing and the rhythms of different types of melody were developed alongside social dances that have been an integral part of Irish culture for many years. Irish music is part of an oral tradition and is commonly learned by watching and listening to other players. Many traditional players do not read music and feel that learning a tune by ear imparts stylistic nuances along with the actual notes of the melody (Boullier, 1998).

Stylistic features are an important way for musicians to individualize their playing on melody instruments. Mastery can be demonstrated through judicious use of ornaments, notes that are not part of the simplified or written melody but form part of a playing style based on the musician's influences, experience and technical ability on their instrument. Ornaments and melodic variation are important musical features. Ornaments have an effect on phrasing and are part of articulation, influencing how a note is started, sustained or ended. Amongst experienced players their use is often idiosyncratic, transferred as part of the teaching process. Such players are able to vary melodies and rhythms in a similar way to changing speech patterns and accents (Lornell and Rasmussen, 2016).

Timbre is also an important feature and instruments such as fiddle and flute allow the player to have control over tonality. In the case of flute playing the embouchure, or use of facial muscles and lip position, are key to achieving a clear and stable tone (Larsen, 2003).

2.1 Flutes, tin whistles and low whistles

Traditional folk instruments like the fiddle, uilleann pipes, whistle and flute are used to play ITM alongside later additions to the tradition such as guitar, bouzouki, banjo and accordion. Melody instruments sound the tune whilst chordal and percussion instruments provide backing. Tunes within the standard corpus of Irish traditional music are written in D major, G major or modal scales using the notes contained in these scales (Ó Riada, 1982). This allows diatonic instruments (e.g, tin whistle, unkeyed flute) to play alongside chromatic instruments like the violin.

> *They may play a tune down a fourth to fit it conveniently on an instrument, or up a fifth for greater brilliancy on the fiddle, but the additional sharp so introduced affects only the middle finger on the second string and the index on the left hand of the bagpipes. It involves merely the playing of the third string on the second and the second on the first, and so the finer adjustment of the fingering need not be applied to new places, or two whole complicated systems of fingering need not be learned* (Henebry, 1928).

The transverse or side-blown flute commonly used by Irish traditional players is made from hard-

Figure 2.1: Rudall and Rose 8-key flute 1832-1850. ©Ganainm 2000 licensed under CC BY-SA 3.0.

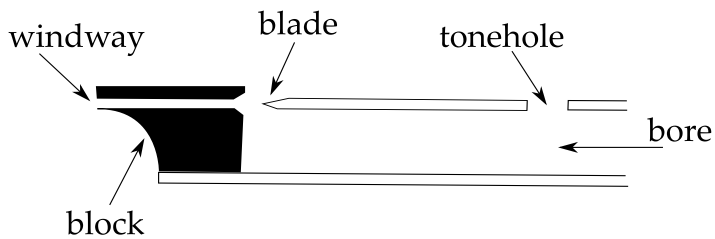

Figure 2.2: Cutaway view of a tin whistle showing windway, blade and one of six toneholes along its length.

wood, typically African blackwood though cocus and grenadilla are also popular. It is commonly known as the concert, Irish or wooden flute.

Since the 1300s, the wooden flute has undergone development and early in the nineteenth century the eight-keyed conical-bored flute had become the norm. Voiced in D, the concert flute had six keys with which to play accidentals and two keys to extend the range down to C# and C, as shown in Figure 2.16.

The most respected flute makers amongst Irish traditional flute players were based in England and started to manufacture flutes around 1820. They specialised in models with a wide bore and large finger holes which resulted in a louder sound. Rudall & Rose (see Figure 2.16) are the best known maker from around this time and many modern flutes are based on either their designs or that of a later flute made by the Boosey company known as Pratten's Perfected, as it was sponsored by a famous player of the time, Robert Sydney Pratten (See Section 2.3.1).

The tin whistle or penny whistle is a fipple flute, where the sound is made by blowing through a windway or duct on to a blade or labum (See Figure 2.2). The oscillation of pressure creates a standing wave at a particular frequency depending upon the length of the tube. The frequency is changed by covering or uncovering toneholes along its length, thus changing the effective length of the bore.

Bone fipple flutes excavated in Dublin date back to the 12th Century but the modern tin whistle is derived from the flageolet (see Figure 2.3), a wood or metal woodwind instrument that was produced

Figure 2.3: A nineteenth Century French wooden flageolet, ©BenP 2006, licensed under CC BY-SA 3.0.

Figure 2.4: High D tin whistles manufactured by (from left to right) Clarke Sweetone, Shaw, O'Brien, Reyburn, Generation, Copeland and Overton. ©Daniel Fernandez 2006, licensed under CC BY 3.0.

from the late 1700s (McCullough, 2000; Vallely, 2011).

The tin whistle is regarded as one of the most popular instruments in traditional music today but in its modern form it dates back only to the early 1800s when tin plate whistles (see Figure 2.4, Shaw whistle) were first made in Britain (Vallely, 2011). The early designs were conical and rolled from sheet metal, the block being made from wood. Injection moulding of plastics made it possible to mass manufacture whistles at a cheaper production cost and resulted in the Generation and Clarke Sweetone designs (see Figure 2.4). Whilst originally a low-cost instrument, there are now many high specification models that offer better tuning and playability, including the O'Brien, Reyburn, Copeland and Overton models shown in Figure 2.4. The Generation whistles are particularly popular and used by many excellent players including Mary Bergin (Manning, 1994).

The tin whistle is a diatonic instrument and available in several keys though high D is the most widely used, having a range of notes one octave above an unkeyed concert flute.

Many flute players also play the whistle as the finger patterns used to create different notes are the same on both instruments. It is also seen as a good beginner's instrument for traditional flute players as it does not require the musician to create an embouchure. The range of ornaments played on the flute are also part of the tin whistle tradition and may be played by using the same finger movements.

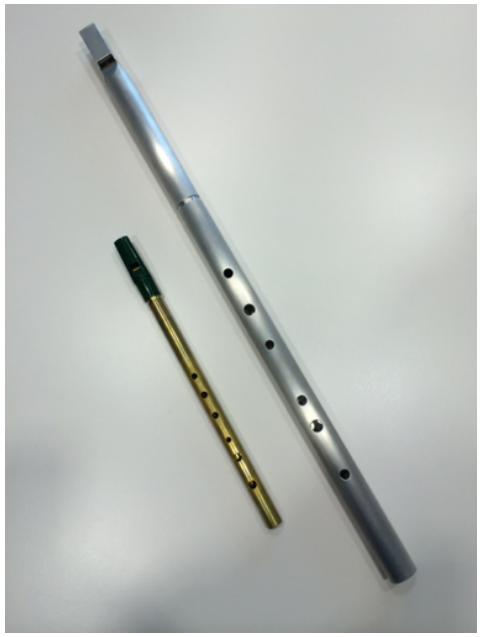

Figure 2.5: Overton low D whistle with high D tin whistle for comparison. ©Kmarty 2014, licensed under CC BY 4.0.

The low whistle is a large tin whistle that plays notes at the same frequencies as the unkeyed concert flute and an octave below the tin whistle. The instrument was developed in 1971 by Bernard Overton, an English engineer and musician, for Finbar Furey who commissioned whistles in A, G and then D. Overton's aluminium design (see Figure 2.5) is still well-regarded though there are now many manufacturers worldwide, the majority being in Ireland, Britain and the United States of America (Hannigan and Ledsam, 2000).

2.2 Categorisation and structure of tunes

A number of tune types appear in the collected recordings and are popular within ITM played in sessions and for dances. These can be classified by time signature and tempo. Although this is not an exhaustive list of all available tune types, it gives a description of common forms. The regularity of music for dancing dictates that the number of bars must fall into multiples that are regular and easy to extend in time through repeating. Most of the examples presented are 32 bars long (two parts of 8

Figure 2.6: Donnybrook Fair, an Irish double jig. Typeset using abcm2ps (Jef Moine, Guido Gonzatto, 2014) by FolkTuneFinder.com, Joe Wass 2016.

repeated bars).

2.2.1 Jig

The jig the oldest form of Irish traditional dance still in popular use. The double jig is the most common form of jig and three other forms of jig exist, namely the single jig, slip or hop jig and the slide.

Hast and Scott (2004) define the double jig as having a 6/8 time signature (see Figure 2.6) where the character of the melody is defined by two groups of three eighth notes. Mnemonic phrases are often used to aid learning of rhythm. Brennan (2001) and Hast and Scott (2004) describe the phrase "rashers and sausages" being used to characterise a double jig.

The character of the single jig is based on a quarter note followed by an eighth note (see Figure 2.7). An example of this is the popular song "Pop goes the weasel". Phelan (2014) documents the Irish harper Turlough O'Carolan as writing pieces of music entitled jiga but there is a greater connection to the music of England, where dance melodies in 6/8 had been commonplace for a long time. John Playford's collection entitled "The English Dancing Master", first published in 1651, includes tunes

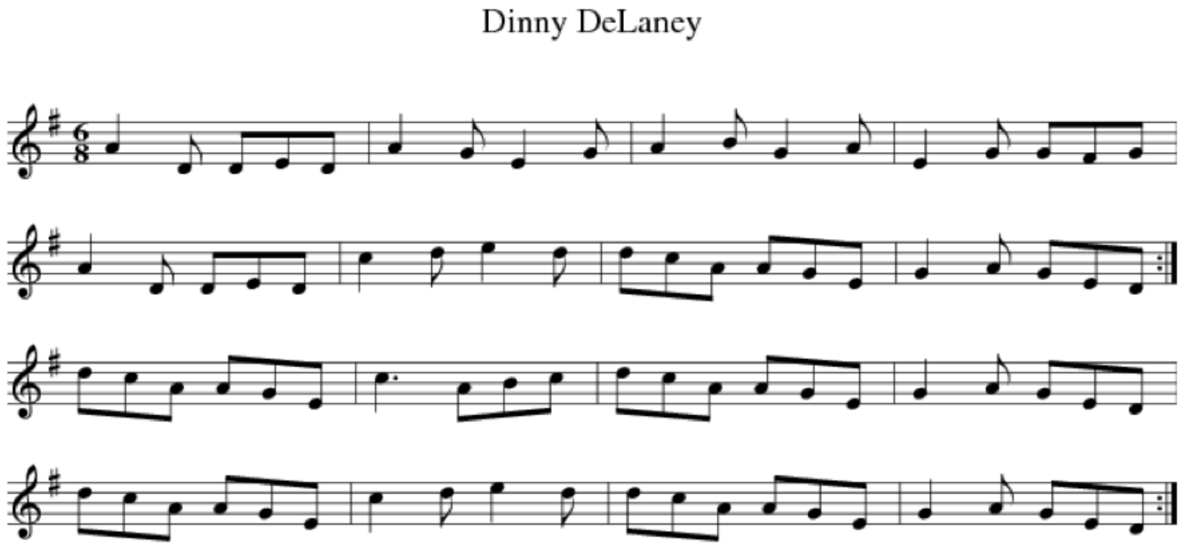

Figure 2.7: Dinny DeLaney, an Irish single jig. Typeset using abcm2ps (Jef Moine, Guido Gonzatto, 2014) by FolkTuneFinder.com, Joe Wass 2016.

with titles such as Kemps Jegg and Millisons Jegge (Playford, 2007). Some earlier Irish jigs came from ancient clan marches and songs but most were composed in the eighteenth and nineteenth centuries (Breathnach, 1996).

Petrie (2005) argued that the slip jig in 9/8 time originated in Ireland and Breathnach (1996) agrees that the tune type was very popular but concludes that the form of tune was also prevalent in England and appears in several printed collections. Drops of Brandy, a well-known slip jig, is shown in Figure 2.8.

The slip jig time signature of 9/8 is categorized by three groups of three eighth notes, often mnemonically described with the phrase "Jesus and Mary and Joseph and" in repetition.

The slide is not as common as the other jigs and emanates from Sliabh Luachra, an area of Munster that borders Cork, Kerry and Limerick. Typically in a 12/8 time signature, the slide follows the rhythmic feel of a single jig with a significantly faster tempo (Hast and Scott, 2004).

2.2.2 Reel

The reel is the most common form of Irish traditional tune. Originating as the reill in Scotland during the sixteenth century, it had emerged in its modern form in Ireland during the eighteenth century. Older reels are typically of Scottish origin, including Miss McLeod's (see Figure 2.9), and many remain staples of the traditional corpus. By the end of the eighteenth century, Irish reels were

Figure 2.8: Drops of Brandy, an Irish slip jig. Typeset using abcm2ps (Jef Moine, Guido Gonzatto, 2014) by FolkTuneFinder.com, Joe Wass 2016.

being printed as part of tune collections in Dublin (Breathnach, 1996; Hast and Scott, 2004).

2.2.3 Hornpipe

The collection of English melodies published in the 1651 edition of Playford (2007) contained a number of hornpipes, but the heavily swung hornpipe of the Irish traditions did not appear until the 1760s (Brennan, 2001). During this time there was also a change in time signature from 3/2 (triple time) to 4/4 (Breathnach, 1996). O'Shea (2008) discusses a typical traditional Irish tune repertoire in the 1870s as having undergone an expansion in the number of reels and hornpipes, partly due to the related dances gaining popularity.

The hornpipe shares its 4/4 meter with the reel but is characterized by a slower tempo and a heavily dotted or swung rhythm (Hast and Scott, 2004). The rhythm is usually notated without showing the dotted rhythm, as shown in The Rights of Man (Figure 2.10).

2.2.4 Polka

As a dance, the polka developed in Czechoslovakia in the early 1800s, emulating Polish dances and becoming widely fashionable in Europe. Upon its introduction to Ireland in the late 1800s, it became particularly common in the south west of the country including Cork, Kerry, Limerick and Sliabh Luachra (Brennan, 2001; Hast and Scott, 2004; Williams, 2010).

The polka, as shown in Figure 2.11 is written in 2/4 time and comes from the older single reel. One bar of a polka will often consist of two groups of two quarter notes, with an accent on the second

Figure 2.9: Miss McLeod's reel, an example of a Scottish reel that is common in Irish traditional repertoire. Typeset using abcm2ps (Jef Moine, Guido Gonzatto, 2014) by FolkTuneFinder.com, Joe Wass 2016.

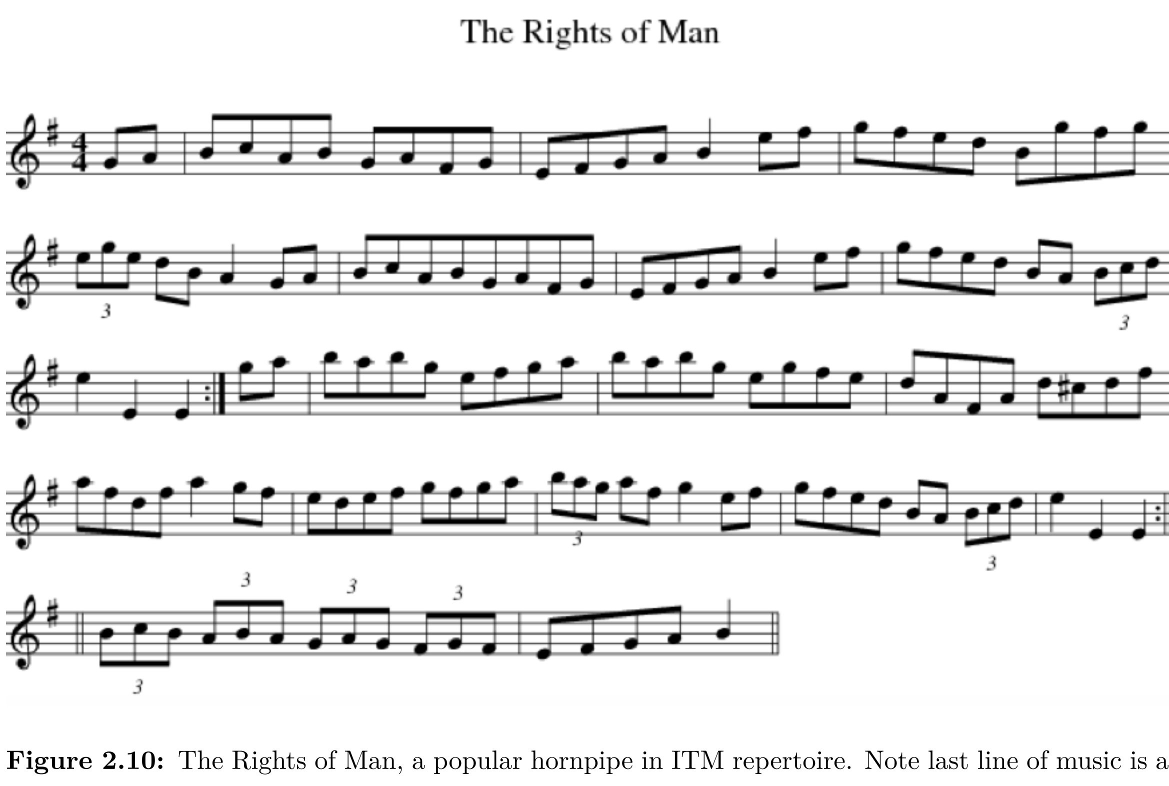

Figure 2.10: The Rights of Man, a popular hornpipe in ITM repertoire. Note last line of music is an alternative setting of first two bars showing how triplets can be incorporated into the rhythm. Typeset using abcm2ps (Jef Moine, Guido Gonzatto, 2014) by FolkTuneFinder.com, Joe Wass 2016.

Figure 2.11: Denis Murphy's Polka, a well-known tune in Irish traditional repertoire. Typeset using abcm2ps (Jef Moine, Guido Gonzatto, 2014) by FolkTuneFinder.com, Joe Wass 2016.

Figure 2.12: Metal flute with Böehm system keywork (disassembled in case) ©J.P.Lon 2009, licensed under CC BY 3.0.

note of each pair. Polkas are not normally swung and all quarter notes are of equal length (Cooper, 2010)

With the introduction of Böehm's flute, the subsequent decrease in the price of wooden concert flutes in the mid to late 1800s made it an affordable instrument for the Irish traditional musician. The wooden concert flute was designed around the key of D, whereas the Böehm system flute is based around the key of C, both using using keys to access other, accidental notes. The open-holed concert flute was easily playable in the keys of D, G and the related modes. Open holes made stylistic ornaments, comprised of fast finger articulations, possible, allowing the flute to take its place as a "pure drop" traditional Irish instrument trading ornaments and other stylistic nuances with the uilleann pipes and the fiddle.

Figure 2.13: Timeline showing major changes in transverse flute design, 1500–1900.

2.3 Development of the modern concert flute

The transverse flute has been found in many historical civilisations. Flutes have been discovered in Japan, China, India and Egypt that date back many thousands of years. The Chinese Tsche, a bamboo instrument with an embouchure hole in the centre and three tone holes on either side, dates back to before 2500 BC. The Ancient Greeks blew across the ends of reeds to create single-note flutes and developed pan pipes or syrinx. The Ancient Egyptian Nay or Ney was an end-blown flute depicted on tomb walls more than 2000 years ago (Haarmann, 2014).

The transverse flute has undergone an almost continuous development cycle since the first written record in the 1300s, (see Figure 2.13) when Guillaume de Machaut described the instrument as being used in his compositions. By 1500, the transverse flute was well-established and could be found in Switzerland, Germany and France. By 1600 there are records of tenor flutes pitched in D (see Figure 2.14) being used as part of flute ensembles alongside descant and bass instruments. The tenor flute was cylindrical and made from a single length of timber with a round embouchure hole and small tone

Figure 2.14: Tenor Flute by Martin Wenner ©Tamie49 2014, licensed under CC BY 3.0.

Figure 2.15: Baroque Flute by Boaz Berney, after an original by Thomas Lot, Paris ca. 1740. Parts are (from left to right) headjoint, middle joint and footjoint with single key. Extra middle joint is longer and lowers instrument by one semitone (from A=415Hz to A=392Hz) ©Aviad 2001, licensed under CC BY 3.0.

holes (Lorenzo, 1992). Smaller toneholes are less accurate when overblown but allow the flute to be played chromatically with the use of cross-fingering (Kite-Powell, 2007).

A family of instrument makers named Hotteterre working at the court of King Louis XIV in Paris, France around 1680 developed a conically bored flute with a cylindrical headjoint bore. Around this time, the flute was also standardised to the key of D major. The design became known as the Baroque flute and the instrument shown in Figure 2.15 displays evidence of these features. Initially the redesigned footjoint was one-piece but later changes, as shown in the illustration, modified it to two pieces making a four-piece flute. The flute was also characterised by a single key on the footjoint, allowing the player to sound a note one semitone above the lowest note (Hamilton, 1990).

At this time, other accidental notes were produced by partially covering holes, or half-holing notes. This proved to be ergonomically difficult for players and required altered fingering patterns for different designs of flute. The notes were also tonally weak and frequently out-of-tune (Lorenzo, 1992; Nederveen, 1998).

By 1800, the concert flute had been further refined to be fully chromatic. The five-key design favoured by French makers augmented an unkeyed flute that played a scale of D, allowing a tonally accurate D#, F G#, Bb and C. English and German makers favoured an eight-key design, adding to the five-key layout with a second “long” F accessible with the fifth digit of the left hand as well as a C

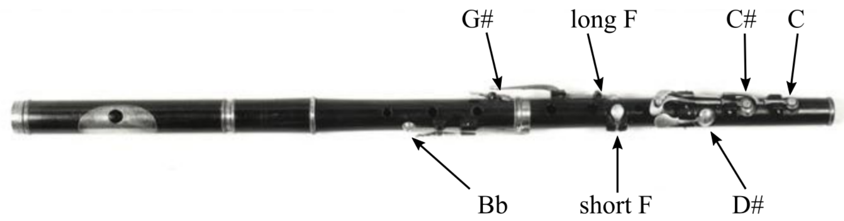

Figure 2.16: Rudall & Rose 8-key flute 1832–1850 showing accidental key notes. ©Ganainm 2000 licensed under CC BY-SA 3.0.

and C# below the D (see Figure 2.16). These instruments are commonly referred to as simple system flutes.

Although unkeyed, five-key and eight-key concert flute designs are standard in Irish traditional music, by 1900 the metal Böehm system flute had become the standard for classical and romantic music. Wooden concert flutes were available at a greatly reduced price in the late 19th century as many players exchanged them for metal flutes. Concert flutes are suited to the playing of ITM because the main six tone holes do not have keys and it is therefore easier for players to execute the quick finger articulations associated with ornaments.

2.3.1 Instrument design

The design of the concert flute has not changed significantly since the 17th century when it moved from parallel to conical bore. A number of small improvements, both acoustical and mechanical have refined the original designs. These include the development of a tuning slide to counteract the effects of heat and moisture in the bore of the flute, improvement in embouchure hole profiles and the use of polymer headjoints to prevent cracking. Figure 2.17 shows the parts of the flute with further detail in Figure 2.18 showing the position of the tenon joints and Figure 2.19 showing the sliding mechanism that allows fine tuning of the flute.

Most traditional flute players prefer to play the simple system or concert flute and these can be classified into two categories: pre-Böehm simple system flutes and modern simple system flutes. In the years preceding the introduction of Böehm's design the flutes manufactured in the mid to late 19th century, mainly in Germany and England, represented two different styles of instrument. The German flutes were factory-made with a relatively narrow bore and small tone holes. German flutes from this era are typically overlooked by ITM players as they do not produce a powerful enough sound (McGee, 2010).

English flutes from 1820 onwards, however, have an excellent reputation among ITM players. The

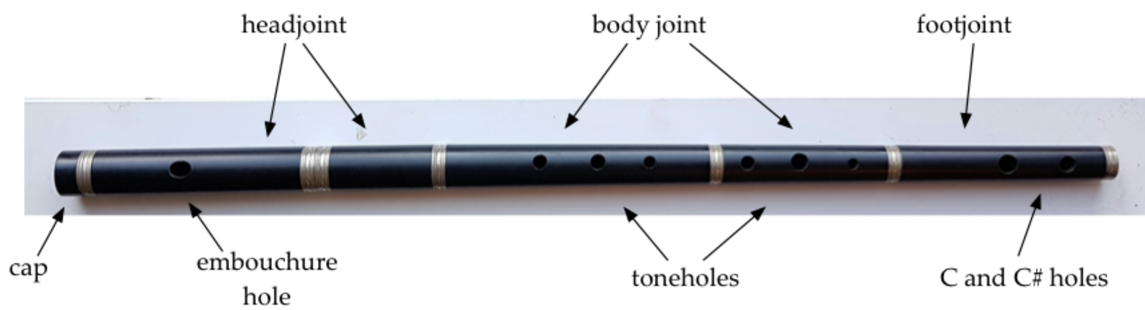

Figure 2.17: Unkeyed Rudall & Rose polymer flute manufactured by M&E flutes.

Figure 2.18: Disassembled unkeyed Rudall & Rose flute manufactured by M&E flutes.

Figure 2.19: Disassembled headjoint showing brass tuning slide and oval embouchure hole, from Rudall & Rose flute manufactured by M&E flutes.

Figure 2.20: 5-Key Pratten, African blackwood body with polymer headjoint, manufactured by Glenluce.

English style of flute from this period has a wide bore and large tone holes. Although there were many flute makers in London at this time, Rudall & Rose are the best known and derivatives of their original design is still widely manufactured by current flutemakers. A later design known as Pratten's Perfected was sponsored by a leading flute player of the day, Robert Sydney Pratten. Pratten's design used a wider bore and larger tone holes than that of the Rudall & Rose (Vallely, 2011).

The rising popularity of the flute in ITM in the 1950s and 1960s made it difficult for players to acquire good quality simple system flutes as they were no longer made by flutemakers who had adopted Böehm's design. The shortfall of simple system flutes resulted in the emergence of Irish flutemakers in the 1970s manufacturing mostly copies of Rudall & Rose and Pratten designs. At the time of writing, this trend has continued and manufacture has spread to the British Isles, America where there are large numbers of Irish people, and France where the concert flute is widely played in Breton traditional music. There are also a large number of Asian mass-manufactured instruments being imported. Many makers continue to manufacture from historic patterns but others have developed innovative designs and used modern materials in production (Vallely, 2011).

Examples of modern versions of classic flutes include the unkeyed Rudall & Rose (see Figures 2.17, 2.18 and 2.19) manufactured by Michael Cronnolly of Co. Mayo, Ireland and the 5-Key Pratten's Perfected Glenluce manufactured in Pakistan (see Figure 2.20).

2.3.2 Notes

Harmonic partials or modes are multiples of the lowest frequency present in a note. These are not to be confused with musical modes, or scales, used to define the individual notes that make up a musical scale. This lowest note frequency is referred to as the fundamental frequency or F_0. Woodwind instruments achieve different notes by enclosing an air column where the lowest note is a standing wave based on the mode 1 vibration of the whole tube or air column in combination with mainly modes 2, 3 and 4 though there is also evidence of higher modes. The low register of the simple system flute, notes D to C# identified in Figure 3.12, is obtained by opening holes along the tube in order to successively shorten the tube length. The second playing register, notes d to b in Figure 3.12, is obtained by overblowing or increasing the velocity of air passing the embouchure hole in order to play a tone based on mode 2. As mode 2 has a frequency twice that of mode 1, the resultant difference between the modes is an octave when both modes are played with the same finger positions (Benade, 1990).

Notes other than those shown in Figure 2.21 can be played in two ways on an unkeyed flute, by half-holing or partially covering a hole or by alternate fingerings that change the intonation of the flute (Maclagan, 2009).

Fingers are often referred to alongside the holes they cover on a simple system flute (see Figure 2.22) (Larsen, 2003). This nomenclature is used as standard throughout this document.

2.3.3 Keys

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The development of specific holes for these other notes and their respective metal keys began in the 16th Century when attempts were made to extend the range of the flute downwards. The flute had the worst intonation of the woodwind instruments and a single instrument was not able to play in tune in the range of pitch standards required in different cities and countries. This led to the development of a multi-part instrument (see Figure 2.18) and a cork that sealed the headjoint and could be manipulated more accurately. A feature of the Baroque flute was the single Eb key (see Figure 2.15), required as this note could not be produced by half-holing or alternate fingering (Toff, 2012).

In the mid-18th Century, the introduction of equal temperament meant that each of the twelve semitones had a definitive frequency. Notes with alternate fingerings had sounded timbrally different from those produced using standard fingerings. The use of dedicated keys ensured a more consistent tone between notes and by the end of the 18th Century, up to 6 keys were in use (Duffin, 2008).

2.3.4 Musical modes and scales

There are approximately 9000 melodies in the ITM corpus (Wallis and Wilson, 2001). Accomplished Irish traditional musicians may have a repertoire of several hundred tunes (Duggan, 2007) and for flute players, most of their repertoire will be playable on an unkeyed flute. Tunes written on other instruments may require modification for flute, an example being fiddle tunes that use the lowest tuned string. The notes in first position on this string too low for the flute and are commonly played an octave above written.

Musical modes are used to describe scales of notes that start on a different scale tone, thus changing

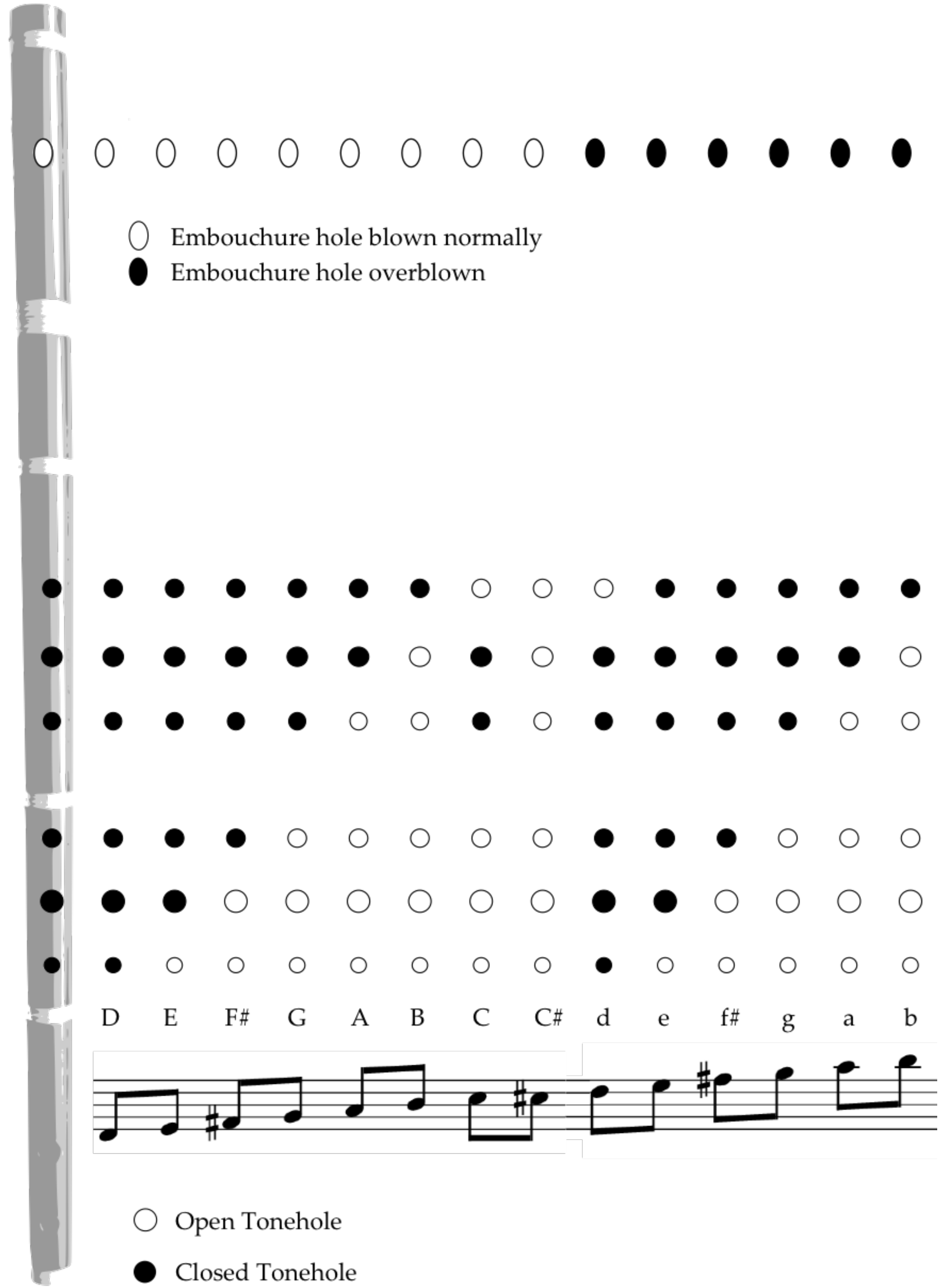


Figure 2.21: Unkeyed simple system flute range, showing normal blow or overblow, finger patterns and notes played.

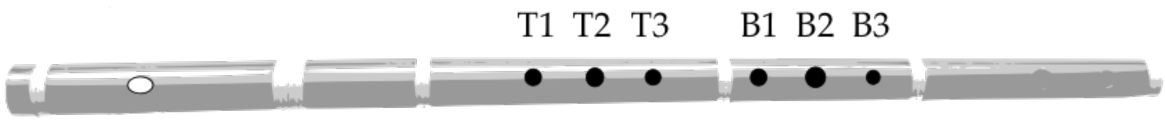


Figure 2.22: Diagram of simple system flute showing names of fingers corresponding to holes they cover.

Mode	Notes							
D Ionian	D	E	F#	G	A	B	C#	D
G Ionian	G	A	B	C	D	E	F#	G
B Aeolian	B	C#	D	E	F#	G	A	B
E Aeolian	E	F#	G	A	B	C	D	E
D Mixolydian	D	E	F#	G	A	B	C	D
A Mixolydian	A	B	C#	D	E	F#	G	A
E Dorian	E	F#	G	A	B	C#	D	E
A Dorian	A	B	C	D	E	F#	G	A

Table 2.1: Common modes and tonal centres found in Irish flute music.

the step relationship between subsequent notes. The use of the term modes in this way is different from its use in acoustic terminology (see Section 2.4.1 where it is used to describe the integer multiple of a fundamental vibrating frequency). The notes illustrated in Figure 2.21 allow the playing of tunes in a number of common musical modes, identified in Tables 2.1, 2.2 and 2.3. The Ionian mode is more commonly known as the major scale and the Aeolian as the natural minor scale. The Dorian mode is similar to the natural minor scale apart from the sixth note in the scale, which is a major sixth above the tonic rather than a minor sixth.

The addition of a G# note (see Table 2.2) either through alternate fingering, half-holing or using a key allows playing in the mode of A Ionian (A major) and B Dorian.

The addition of a F♮ (F-natural) note (see Table 2.3) either through alternate fingering, half-holing

Mode	Notes							
A Ionian	A	B	C#	D	E	F#	G#	A
B Dorian	B	C#	D	E	F#	G#	A	B

Table 2.2: Common modes and tonal centres found in Irish flute music using an additional G# note.

Mode	Notes							
A Aeolian	A	B	C	D	E	F	G	A
G Mixolydian	G	A	B	C	D	E	F	G

Table 2.3: Common modes and tonal centres found in Irish flute music using an additional F♮ note.

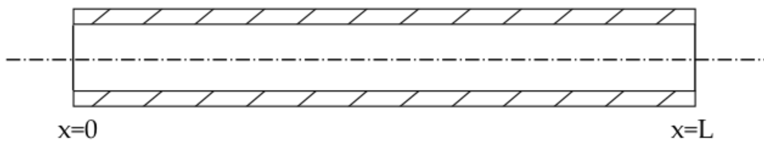


Figure 2.23: Simple acoustic approximation of a flute.

or using a key allows playing in the modes of A Aeolian (A minor) and G Mixolydian.

2.4 Flute acoustics

This section details the acoustic properties of the flute, how they can be measured and ultimately, optimum methods for capturing recordings of them.

2.4.1 Acoustics of a cylindrical tube

The acoustics of the flute can be calculated as a cylindrical tube of length L that is open at both ends (see Figure 3.14). The air is free to move in and out at either end causing fluctuations in pressure, resulting in a point where the standing wave is reflected known as the pressure node.

The theoretical position of the pressure node is approximately 0.3 of D, the diameter of the tube, away from the end of the tube. In a tube where both ends are open to atmospheric pressure, L_{eff} or the effective length (see Figure 2.24) is half the length of the standing wave used to calculate the fundamental frequency. It can be calculated using:

$$L_{eff} = L + 0.6D \tag{2.1}$$

Equation (2.1) is designed for use with lower frequencies, typically in the first mode (see Figure 3.16) because the end correction becomes gradually smaller as the note frequency rises. For overblown notes, the reduced end correction is:

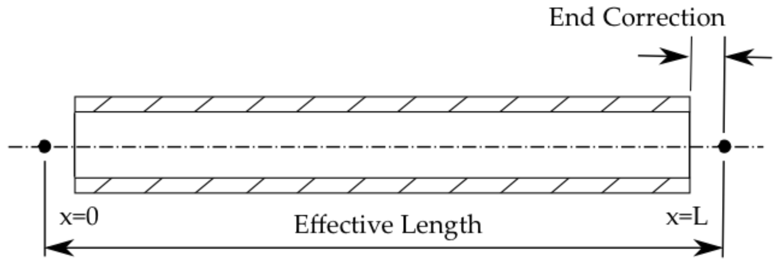


Figure 2.24: Simple acoustic approximation of a flute showing end correction.

$$L_{eff} = L + 0.3D \tag{2.2}$$

The tube is energised by blowing across a hole to create a standing wave with points of air molecule movement and non-movement along the bore. Points of maximum movement are known as antinodes and non-movement points are known as nodes. The lowest vibrational mode is the fundamental or F_0 where there is one nodal point in the middle of the cylinder. As the ends of the tune are always at atmospheric pressure, there will always be antinodes at the extremities of the flute (Nederveen, 1998).

The wavelengths of standing wave patterns are governed by the distance required for the wave to complete a full cycle. The quarter-wavelength distance is calculated from node to nearest antinode. For the first vibrational mode or F_0, the quarter-wavelength is approximately half the length of the tube (Campbell et al., 2006).

The wavelength can be calculated using:

$$\lambda = 2L \tag{2.3}$$

where λ is the wavelength and L is the effective length. The resultant frequency is calculated using:

$$F_0 = \frac{c}{2L} \tag{2.4}$$

where c is the speed of sound.

The modes shown in Figure 2.25 are based on a cylindrical tube that is open at both ends. A simple system flute varies from this in two ways, containing an embouchure hole and having a bore that is tapered.

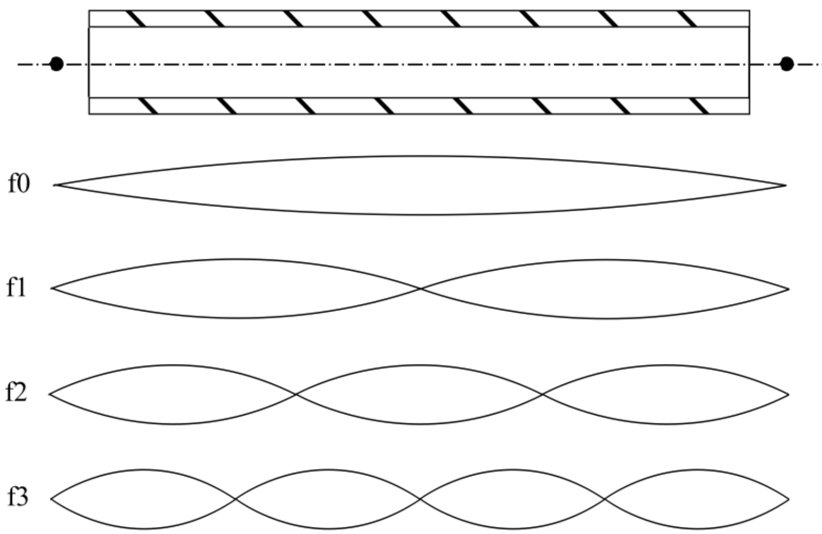


Figure 2.25: Standing wave patterns for a cylindrical tube open at both ends, showing two modes commonly used for notes played in ITM (F_0 and F_1) along with modes F_2 and F_3, also present in many flute notes. Based on an open cylinder of length approximately 66cm, pitch of F_0 is note C4 (261.63Hz) and pitch of F_1 is note C5 (523.25Hz).

2.4.2 Headjoint and internal bore profile

The length of the end correction at the embouchure hole varies according to the distance from the embouchure hole to the cork. By rotating the crown (see Figure 2.26), the screw thread moves the cork closer or further away from the embouchure hole, thus decreasing or increasing the length of the bore. If the cork is positioned just next to the embouchure hole, end correction at 1kHz is approximately 35mm. Moving the cork by 30mm in order to lengthen the bore increases the end correction to 50mm. The overall effect of moving the cork is an expansion or contraction of the frequency ratios in the lower modes, as shown in Figure 2.26 (Campbell et al., 2006).

The headjoint of the simple system flute is cylindrical but the bore tapers from the end of the headjoint to the foot. A measured example of an English flute designed by Nicholson in 1822 is contained in Rockstro (1967). The overall bore length of the instrument from cork to open end is 23.60" (599.44mm) with a headjoint bore of 0.74"(18.80mm) and an open end diameter at the foot of 0.45"(11.43mm). Flutemaker Terry McGee has collected measurements of seven classic simple system flutes that are all within of 17.8mm-18.8mm at the headjoint and 10.7mm-12.9mm at the foot. The flutes include two designs that are still widely manufactured: Boosey & Co's RS Pratten's Perfected and Rudall & Rose's No. 5501. The Pratten has one of the widest bores and the Rudall & Rose has one of the narrowest (McGee, 2016).

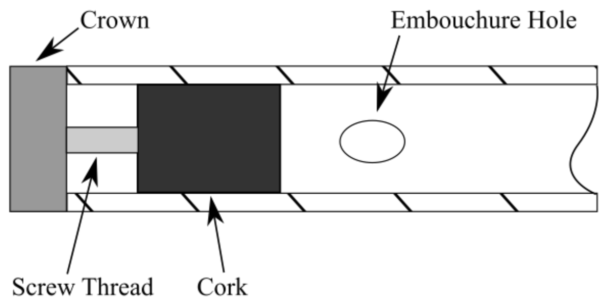


Figure 2.26: Cutaway view of flute headjoint showing position of cork mechanism and embouchure hole.

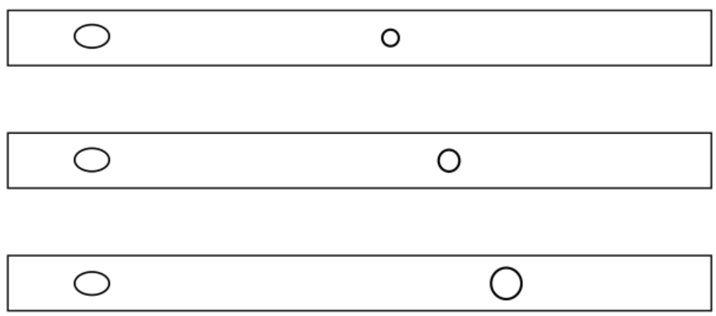


Figure 2.27: A selection of tone hole diameters and positions that will produce the same pitch.

2.4.3 Tone holes, cross fingering and cutoff frequency

In the lower register of the flute, removing fingers from one or more tone holes allows the pressure node in the bore to "short circuit" to open air. The exact wavelength is governed by a number of factors: The dimension of the open tone hole and whether tone holes further down the bore are closed or open. Examples of different hole diameters and positions used to create the same pitch are shown in Figure 2.27.

Higher frequencies behave differently as the pressure node is not able to accelerate the mass of air at the tone hole in order to "short circuit" at the same point and the pressure node travels further down the bore (Wolfe and Smith, 2003). On unkeyed simple system flutes, this allows tone holes positioned downstream of the first open tone hole to be covered in order to produce intervening notes (Wolfe, 2016).

The cutoff frequency is the highest resonant frequency that can be sounded through a particular tone hole. Benade (1990) estimated cutoff frequency F_c using:

$$F_c = 0.11 \left(\frac{b}{a}\right) v \sqrt{\frac{1}{st_e}} \tag{2.5}$$

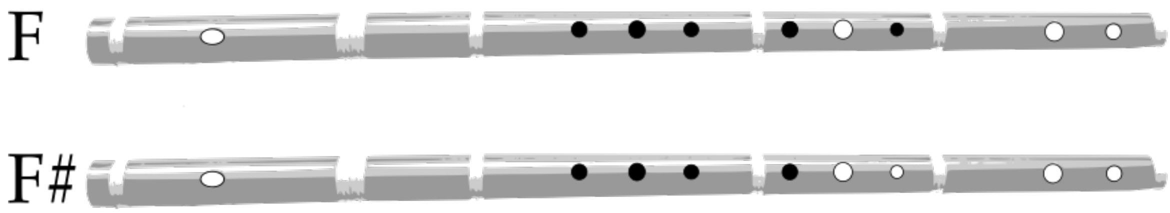


Figure 2.28: Example of cross fingering for F4 and F5 notes compared to fingering of F#4 and F#5 on simple system flute. Note the two holes on RHS of each flute (nearest to foot) are normally open on an unkeyed flute.

where: b = tone hole radius, a = bore radius, v = speed of sound, s = half of spacing between soundholes, t_e = length of a plug of air with inertia equal to a tonehole in a wall thickness t. t_e is approximately equal to $t + 1.5b$.

The radiated sound is dictated by interaction between the vibrating source at the embouchure hole and the open tone holes, also known at the tone hole lattice. At lower frequencies the tone hole lattice acoustically reflects the air column resulting in clear resonant frequencies. At higher frequencies the open holes transmit the acoustic wave without distinct resonant peaks (Fletcher and Rossing, 1998).

A series of experiments comparing cutoff frequencies between baroque, classical and modern flutes show clear differences between the three types of flute. Though there are differences between the cutoff frequency at each tone hole, the results show a mean and standard deviation across the whole instrument. A Baroque flute, based on a design from 1790, has small tone holes and a cutoff frequency of approximately 1.1kHz. A replica of a large-holed Rudall & Rose flute, typical of flutes used in ITM, has a cutoff frequency of around 1.5kHz and a modern Boehm system flute has a cutoff frequency of 2kHz. In each flute, bore resonances are weak above 3kHz as they are equivalent to the Helmholtz resonator formed by the embouchure hole and the distance to the cork (Wolfe and Smith, 2003).

2.4.4 Blowing and overblowing

Helmholtz and Ellis (1875) discovered that any vessel of air can produce a pitched tone if there is a sufficiently small opening and a sharp edge where a stream of air can be directed. As well as a resonance formed by the frequency of the pressure node oscillating in the vessel, wind noises formed from inharmonic tones are produced by air striking the sharp edge.

When a flute player overblows, they are raising the pitch by approximately an octave by changing the air jet vibration from first mode to second mode. As shown in Figure 3.16, the change from F_0

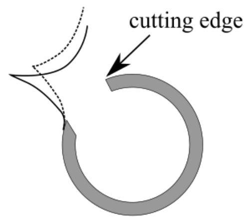


Figure 2.29: Lip position of a flute player showing first mode (solid line) and second mode (dashed line) adapted from Campbell et al. (2006).

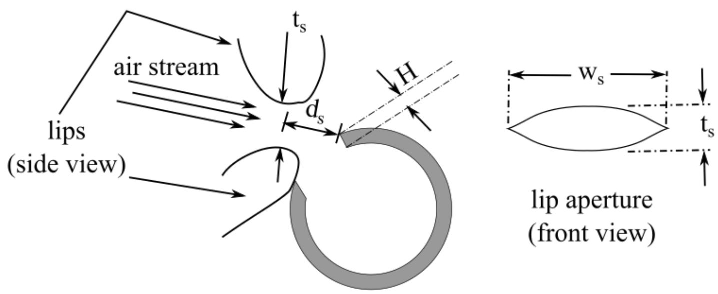


Figure 2.30: Flow-control for air blowing across a flute embouchure hole (Benade, 1990).

to F_1 relates to the wavelength being halved, therefore the frequency is doubled. Two techniques are used in order to overblow. The air jet speed can be increased and the distance between the lips and the cutting edge (see Figure 2.29), also known as the edge-slit distance, can be decreased. It is common practice for both techniques to be used together but moving the lips forward results in greater coverage of the embouchure hole and a larger end correction. The outcome of a larger end correction is a flattening of overblown notes (Campbell et al., 2006). In order to tune the flute for use in the first two modes, the tuning slide is used to tune a lower note and the cork is adjusted to tune notes in the upper mode (Benade and French, 1965).

In a series of experiments using organ pipes, Helmholtz and Ellis (1875) found that blowing these pipes with sufficient force produced harmonics up to F_5 or the 6th partial. It was noted that when transverse flutes were blown softly, the upper partials were not as pronounced and the tone was weaker and softer. Coltman (1968a) continued this work to show the nature of the oscillation at the mouth hole and also to calculate the efficiency of conversion from air jet to acoustic oscillation (see Figure 2.30). Coltman (1968a) found that the phase of the alternating pressure at the mouth hole with respect to the acoustic current depended upon the distance from the lips to the cutting edge d_s and the propagation velocity of a wave on the jet, equal to approximately 0.4 times the air stream velocity. The flute player uses blowing pressure and lip-to-edge distance alongside manipulation of the lip aperture w_s and t_s in order to control the amplitude of the oscillation at the mouth hole. Thus the amplitude of the note is maintained. Benade (1990) discusses the flute player's ability to trade a larger or smaller lip-to-edge d_s distance against changes in air stream velocity, as well as manipulating lip aperture in order to create a range of timbres. As well as being able to produce the first six partials, an experienced flute player can strengthen or weaken the odd partials relative to the even ones, resulting in timbral changes. Describing a flute player blowing an A4 note with a fundamental frequency of 440Hz and partials at 880Hz, 1320Hz, 1760Hz and beyond, Benade (1990) explained the player's ability to change timbre mid-note. In altering the blowing method, the odd-numbered partials (440Hz and 1320Hz) can be weakened to a point where the note becomes an A5 with a fundamental of 880Hz. This technique of changing the strength of partials is often employed in ITM in order to accentuate particular notes and phrases.

2.5 Stylistic features

> In an Irish context, good musicianship implies that you have listened to so much music that you have internalized the blas or "feel" or "taste" of the music. It means, for example, that if you were to encounter a new jig, you would not play the six eighth notes in each measure using precisely the same amount of time for each note. Instead, you would slightly lengthen and shorten the time value of certain notes; you might slur the notes across particular barlines; you might start varying the tune immediately. You might group the phrases with your breathing, your fingering, or your bowing. You might throw in a roll instead of a dotted quarter note. Why? You would do it because it would be the right thing to do in Irish music, and exactly the wrong thing to do in classical music (Williams, 2010).

In order to identify stylistic differences between Irish traditional flute players, it is important to first define the individual components that contribute to an overall style. Breathnach (1996) provides a discussion of this subject area in his chapter entitled Traditional Techniques and Styles. In this section, he outlines a set of "performance rules" that are delivered almost unconsciously by the musician, having been learned by a process of immersion in listening and playing. Breathnach describes the groups of notes in a bar of a reel or jig as being accented in a particular manner that is similar between traditional musicians. In this way the tune is treated as a series of phrases, often four bars long and split into two halves. As the flute takes many stylistic cues from the uilleann piping traditions it is important to note the distinction made by Breathnach (1996) between two major styles of fingering the pipes, open and closed. The open-fingered style more commonly found in the east of Ireland created a more legato sound as notes are able to transition smoothly. The close-fingered style where only the fingers required to sound the note are lifted, creates a more percussive effect where the start and end of each note are more defined. McCullough (1977) defines style as "the composite form of the distinctive features that identify an individual's musical performance." He defines four variables: ornamentation, melodic and rhythmic variation, phrasing and articulation, stating that these standards are judged by other musicians. A performance by an individual musician will depend on their individual aesthetic and this, coupled with contextual information like the type of performance, will lead to an individual style that can be classified with a number of descriptors. The work of McCullough (1977), Ó Súilleabháin (1981) and Breathnach (1996) form a basis for the definition of stylistic components (Keegan, 2010).

Keegan's definition consists of ornamentation, phrasing, articulation, variation, intonation, tone, dynamics, repertoire, duration, emphasis, speed, instrumentation and instrument-specific techniques. In order to analyse and compare the playing style of a number of flute players, it is important to be aware of these stylistic components as part of detection and classification.

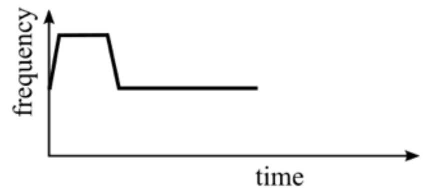
2.5.1 Ornamentation

Ornaments are used to embellish the melody in Irish traditional music. They are central to the style of the music, adding expressiveness. Ornaments are rarely written and are played as a personal preference of the musician, adding to their personal playing style. They can be divided into two classes: fingered and non-fingered ornaments. Fingered ornaments can be classed as single-note comprising of cuts, strikes and slides or multi-note ornaments including rolls, cranns, finger vibrato and trills. Multi-note ornaments take the place of small pieces of melody between one and three eighth notes in length by using finger articulations, rather than adding extra grace or ornamental notes. Non-fingered ornaments include tongue and glottal stops, two forms of interrupting the stream of air, and breath vibrato (Larsen, 2003).

The cut is a single note articulation from a higher pitch. It is performed by starting with the articulation and quickly moving to the main or parent note. The overall effect is a pitch deviation returning to a main note. The cut is performed at a speed where it is not identifiable as having an individual pitch and is a way of articulating a note.

The cut is usually notated as a grace note (see Figure 2.31a), but it should not be treated as such and the articulation should start at the point where the parent note is due to commence. The brevity of the articulation means that the cut is not perceived as a note in itself, but as the leading edge of the parent note (Larsen, 2003). Figure 2.31b shows the change of pitch over time for a cut. A cut may

(a)



(b)

Figure 2.31: Cut, showing (a) musical notation and (b) change of pitch over time. Cut time is approximately 50 ms.

be performed with any finger that is closed to form the main note but the larger the distance between cutting finger and the lowest covered hole, the longer it will take for the pitch to return to the main note. Larsen (2003) recommends using, where possible, the second hole above the top closed hole (see Figure 2.32) though this is not possible on the B note where finger T1 is used. There is no standard fingering for cuts and a more popular layout, used in Vallely (1986) and McCullough (1987), is shown in Figure 2.33.

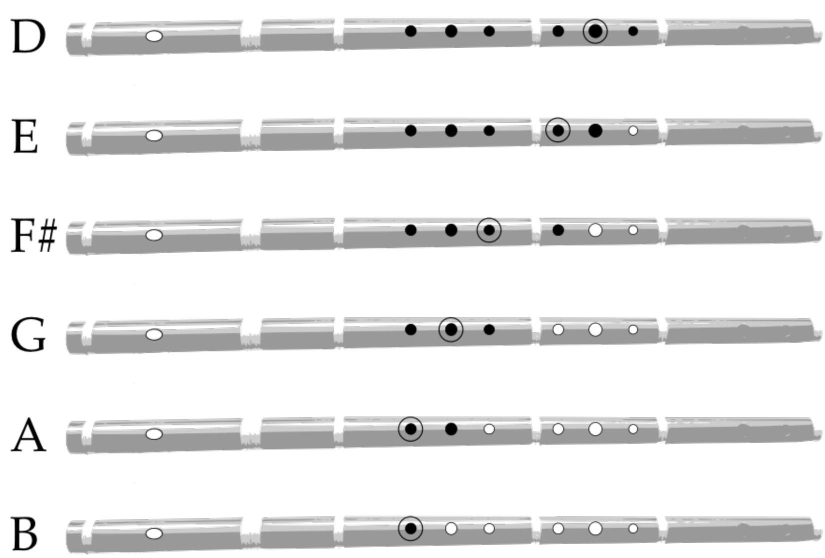


Figure 2.32: Cuts as recommended by Larsen (2003) showing circle on cutting finger and closed holes in black.

The strike is a single note articulation from a lower pitch. The strike is performed by starting with the articulation and quickly moving to the main note. The overall effect, like that of a cut, is a pitch deviation returning to a main note. The strike is also performed at a speed where it is not identifiable

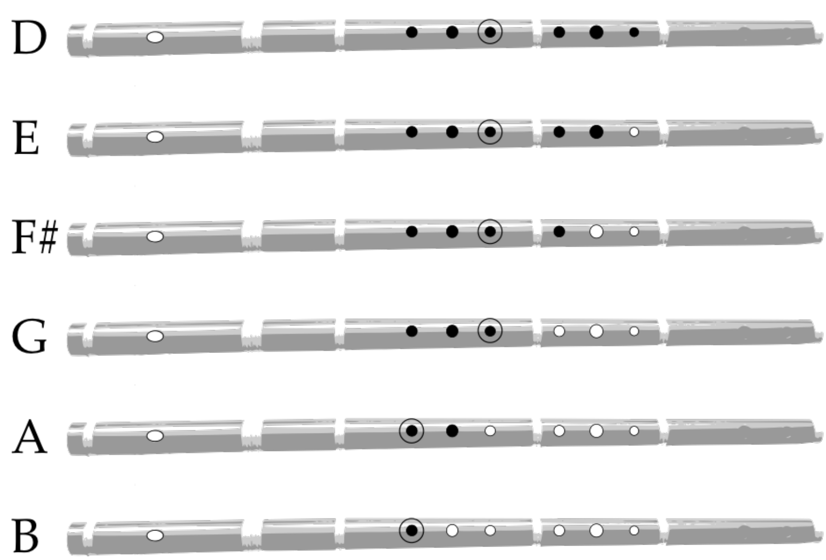
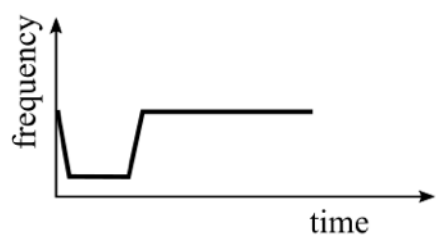


Figure 2.33: Cutting fingers used in a number of tutor books, showing circle on cutting finger and closed holes in black.

as having an individual pitch and is a way of articulating a note.

(a)



(b)

Figure 2.34: Strike, showing (a) musical notation and (b) change of pitch over time. Strike time is approximately 40 ms.

Although the strike, like the cut, is notated as a grace note (see Figure 2.34a) it should not be treated as such and the articulation should start at the point where the parent note is due to commence. The brevity of the articulation means that the cut is not perceived as a note in itself, but as the leading edge of the parent note (Larsen, 2003). Figure 2.34b shows the change of pitch over time for a cut. Due to the finger motion of momentarily covering a tone hole, the strike is also known as a pat or tap. Unlike the cut where there is no universally agreed fingering, the strike is generally performed on the open tone hole directly under the lowest closed hole (see Figure 2.35) apart from note C that uses finger T1 to strike.

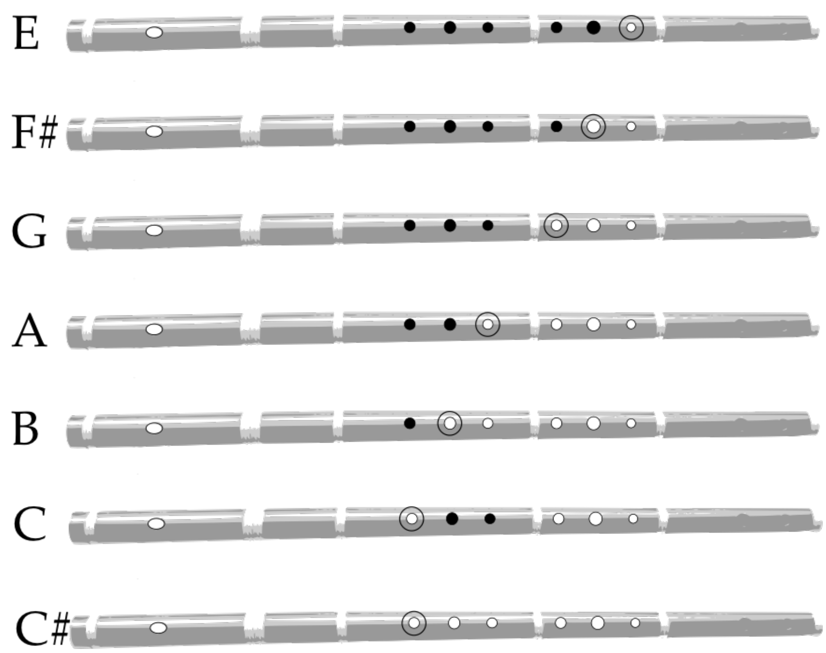
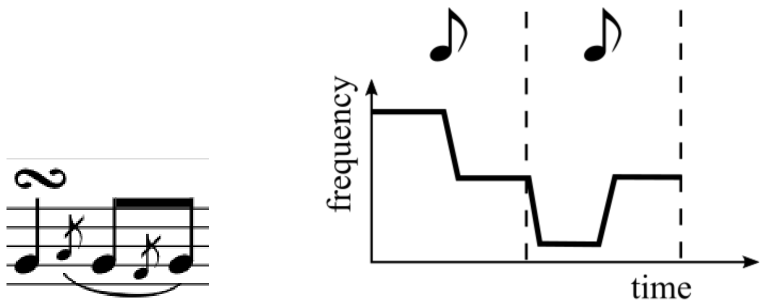


Figure 2.35: Strikes showing circle on striking finger and closed holes in black.

2.5.2 Multi-note ornaments

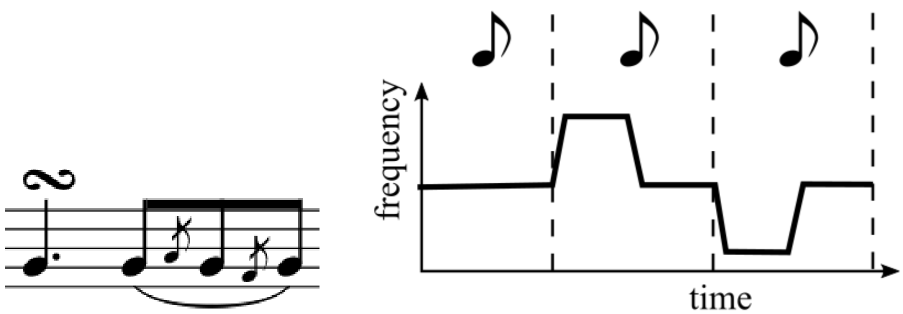
Sections 5.3 and 5.4 present techniques to detect single-note and multi-note ornaments. Multi-note ornaments comprise of single-note ornaments, namely cuts and strikes. The most common multi-note ornaments are rolls and cranns. Rolls can be further classified by length into short rolls (two quavers) and long rolls (three quavers). Larsen (2003) expanded the classification system for rolls and cranns to include a *condensed* variant of each but these have been discounted as they are not widely used. The symbol widely used for a roll is the *turn* symbol shown in Figures 2.36(a) and 2.37(a). Breathnach (1963) uses a crescent to denote the position of a roll. As previously discussed, the playing of such ornaments is considered optional and their use contributes towards an overall playing style.

The short roll (Figure 2.36) occupies the space of two quavers or eighth-notes and is played as a two notes slurred together, the first leading with a cut and the second leading with a strike. The long roll (Figure 2.37) occupies the space of three quavers or eighth-notes and is played as three notes slurred together, the second leading with a cut and the third leading with a strike. The crann (Figure 2.38) consists of three cuts in close succession and was originally a piping ornament, appearing on recordings of Patsy Touhey between 1900 and 1919. It was not widely used as a flute ornament until



(a) **(b)**

Figure 2.36: Short roll, showing (a) musical notation and (b) change of pitch over time.



(a) **(b)**

Figure 2.37: Long roll, showing (a) musical notation and (b) change of pitch over time.

the 1970s although it is occasionally found on earlier recordings, especially of pipers who also play flute and/or tin whistle (Larsen, 2003). As with the roll, short and long variants exist respectively occupying the time of two and three eighth notes. The short crann, like the short roll, omits the first quaver. Cranns are normally used where it is impossible or difficult to play a strike, for instance on the D or E notes. There is no standard fingering for the crann although two popular patterns using standard finger nomenclature (Figure 2.22) are *B2 B1 B2* or *B1 T3 B1*.

2.5.3 Analysis of flute timbre

Most analysis of flute timbre has focused on the cylindrical metal flute, developed in 1847 by Theobald Böehm, as it is regarded as the standard in classical and jazz (Coltman, 1971; Widholm et al., 2001). In comparison to the standard design of metal Böehm System flutes, the wooden or concert flute preferred by traditional Irish players encompasses a range of designs. There are differences in materials, bore profiles and lengths and variances in use of keys, tonehole and embouchure hole dimensions and position.

The role of the instrument in the production of a flute player's overall timbre has been studied on a number of occasions in the context of classical music. Miller (1909) discussed the use of different flute materials and agreed with Böehm (1922) in that "Any variation in the hardness or brittleness of the material has a very great effect upon the timbre or quality of tone." Böehm advocated the use of hard and brittle German silver instead of pewter for a sonorous timbre, remarking that pewter gives a soft and weak tone and wood sounds "literally wooden" (Miller, 1909). Miller (1909) also discusses the work of Mahillon (1874) who theorised that the production of timbre was more closely related to the musician than the material. The work of Backus (1964) and Backus and Hundley (1966) initially developed the argument that wall material and thickness make little difference to the overall timbre of the flute by testing a range of artificially blown instruments. Coltman (1971) tested three unkeyed flutes made from silver, copper and wood and found that listeners, whether musically trained or not, were unable to distinguish between flutes made of the different materials or with different wall thicknesses.

This work was followed up by Widholm et al. (2001) who thought that there was a stigma attached to the work of Coltman (1971) because the flutes were built for the experiment and did not contain any keys. Widholm et al.'s experiments used seven production flutes manufactured by the Muramatsu company and varying in price from 1,000 to 70,000 USD. The instruments were identical apart from their material, being silver coated, full silver, 9, 14 and 24 karat gold, platinum coated and full platinum. Seven professional flautists were recorded in an anechoic chamber playing a chromatic scale over the range of the instrument as well as various notes at different strengths and a piece of music by J. Brahms. The study found that the material used to manufacture a flute has a negligible effect on the overall timbre. The largest difference in the frequency range from 0-16 kHz caused by a material is less than 0.5 dB. However, timbral content varied substantially between players, whilst individuals produce an almost consistent timbre across a range of flutes.

2.6 Chapter summary

This chapter has discussed the development of the wooden traverse flute and outlined the main factors involved in playing the instrument in the traditional Irish style. The evolution of the instrument followed the development of manufacturing technologies as well as European music until the late 1800s when the metal flute was developed. The design of the modern eight-keyed concert flute is often based on key designs from around this time including those by Rudall & Rose and Pratten.

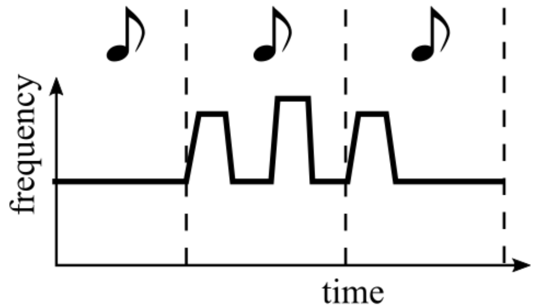


Figure 2.38: Long crann, showing change of pitch over time.

The open-holed nature of the concert flute lends itself to the fast, ornamental playing typical of ITM. Typical melody types are discussed in terms of their time signature and origin. Typical scales and modes are discussed along with the use of metal keys that are added to the flute to allow the playing of extra notes in order to make the instrument chromatic.

Flute acoustics are investigated along with the techniques used to create differing timbres, an important contribution to playing style. Stylistic features are also discussed, in particular detailing production of the notes, single-note and multi-note ornaments that are central to the playing of ITM on the flute.

This information is important as it describes stylistic features that can be detected and analysed as part of a player classification method. The following chapter presents the datasets that were captured including recordings and associated metadata.

Chapter 3

Datasets

3.1 Introduction

Two datasets were collected as part of this study. All tracks include only flute recordings with no accompaniment. The *ITM-Flute-99* dataset is comprised of 99 solo flute recordings of between 16 and 81 seconds in length, spanning over 11 players and 50 years. The *ITM-Flute-Style6* dataset consists of 28 recordings by each of 6 players (168 total). The average duration of all tracks is approximately 43 seconds. The total duration of the dataset is 2 hours.

3.2 ITM-Flute-99

The study of Irish traditional flute playing requires specialised data for training and testing of algorithms. No datasets exist to facilitate this work although recordings of traditional flute players were available. Many of the released recordings of prominent musicians contain accompaniment have been discarded. Metadata was not available for the selected recordings, leading to the development of a methodology for manual annotation. The *ITM-Flute-99* dataset is comprised of 99 solo flute recordings of between 16 and 81 seconds in length, spanning over 50 years. Player, tune title, recording source, tune type and key are identified in Table 3.2. Table 3.3 shows each tune from the *ITM-Flute-99* dataset alongside its use in published papers.

Annotations associated with this dataset include the temporal location of onsets and the event type (e.g., note, ornament). The annotation method is described in Section 3.2.2. The software used for annotation was first Sonic Visualiser (Cannam et al., 2010), and then Tony (Mauch et al., 2015) and these are identified in Table 3.4 alongside information on the lowest note and pitch of the flute used to play on each recording. During the annotation process, additional classes such as breaths were included in the note class as they contained pitch information from a previous note. The annotated event types are represented by 15,310 notes, 2,244 cuts and 672 strikes.

The recordings chosen for analysis are part of a corpus of flute melodies, selected from commercially available sources and assembled under an AHRC Transforming Musicology project (Köküer et al., 2014b). The initial corpus that formed the core of *ITM-Flute-99* featured the solo flute playing of Harry Bradley, Matt Molloy, Conal O'Grada, Séamus Tansey and Michael Tubridy who are prominent musicians in Irish traditional music.

3.2.1 Players

The flute players and their key residences are shown in Figure 3.1. They represent professional players from a range of geographical locations in Ireland. Although globalisation and the recording industry has had a strong effect on regional music styles there still remains a sense of local and regional identity that translates to music (Kearney, 2012). Ó Riada (1982) describes the Sligo flute style as containing irregular phrases that are broken up more frequently than in other regions but that Séamus Tansey sounds more like a Co. Clare player as he uses longer phrases and more ornaments, though his playing has a rhythmic style associated with Sligo. Keegan (1992) agrees with the Sligo style being rhythmic although overuse of ornamentation is uncharacteristic of this area. Vallely (2011) suggests that the Sligo style can be ornate but is also characterised by a rhythmic push or puff at the start of each phrase. This can be heard in the playing of Séamus Tansey and Matt Molloy (Duggan, 2009). In Köküer et al. (2017), Daithí Kearney describes Michael Tubridy as also having a strong Co. Clare style. Matt Molloy's playing is particularly ornamented and has roots in the North Connacht traditions that trace their existence to marching bands from around this area. Matt Molloy is a well-known flute player, coming to prominence in the 1970s in the Bothy Band and Planxty before joining international touring act the Chieftains in 1979. Dowling (2014) discusses Matt Molloy's playing, noting that the influence of his style can be "heard everywhere". Conal Ó Grada's playing is aggressive and rhythmic, influenced by the Sliabh Luachra style of polkas and slides. He is particularly known for his use of glottal stops (Cooper, 2010). Harry Bradley was born in Belfast and has lived in Cork, Dublin and Galway. His playing is rhythmical and uses pulses in breathing to accentuate particular notes and phrases.

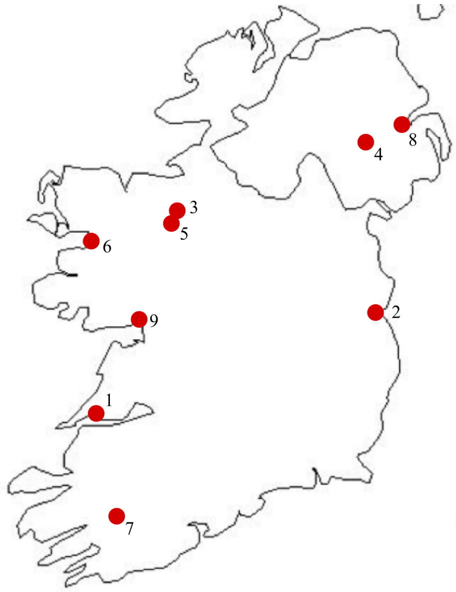


Figure 3.1: Geographical location of players included in dataset. 1) Kilrush, Co. Clare, Michael Tubridy; 2) Dublin City, sometime residence of Matt Molloy and Michael Tubridy; 3) Gorteen, Co. Sligo, birthplace of Séamus Tansey; 4) Craigavon, Co. Armagh, residence of Séamus Tansey; 5) Ballaghaderreen, Co. Roscommon, Matt Molloy birthplace; 6) Westport, Co. Mayo, Matt Molloy's pub; 7) Cúil Aodha, Co. Cork, Conal Ó Grada; 8) Belfast, Co. Antrim, Harry Bradley birthplace; 9) Galway, Co. Galway, Harry Bradley residence. (Köküer et al., 2017).

3.2.2 Manual annotation

The original stereo recordings, sampled at 44.1kHz with 16 bits, are converted, by summing the channels, to mono audio. Manual annotations are then created by inspecting the signal using the Sonic Visualiser tool (Cannam et al., 2010), loaded with the Aubio Pitch Detector and Aubio Note Detector plugins (Brossier, 2006), as well as by listening by the author, who is also an experienced player of Irish traditional flute. During annotation, the notes were also checked by playing the same melody on a flute. The Aubio Note Detector was also used as a playback device to check that the ground truth annotations matched the original recording both in timing and pitch. Figure 3.2 shows a screenshot from Sonic Visualiser depicting an excerpt from The Shaskeen played by Grey Larsen, Tune No.98 in Appendix A (Section 3.2). Both the waveform (top) and the spectrogram (bottom) are superimposed with manually drawn ground truth annotation.

The annotation indicates segmentation of the audio signal, where each segment includes the following information: time of onset, time of offset, type of segment, note identity, note frequency. The type

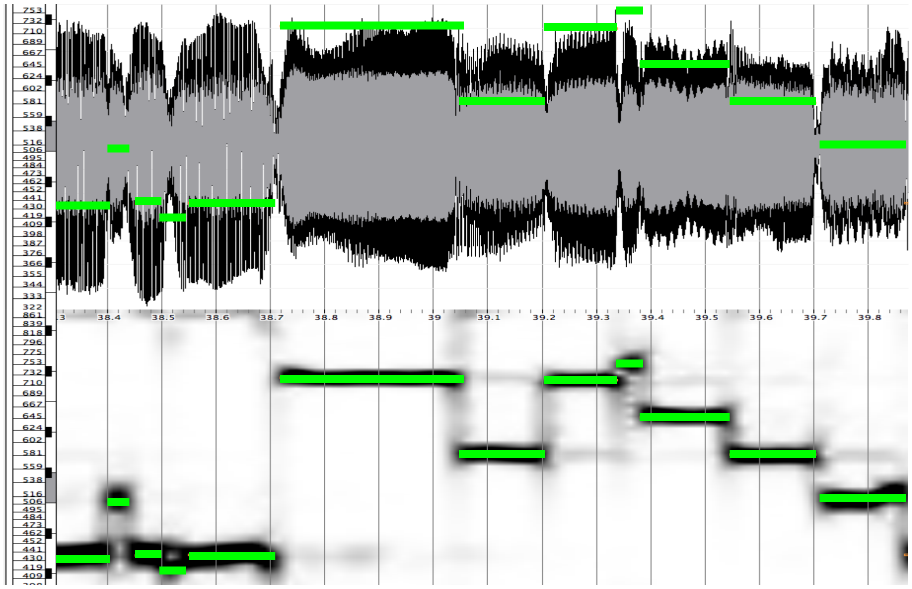


Figure 3.2: An example of a screenshot from Sonic Visualiser depicting the waveform and spectrogram with indicated manually annotated notes.

of segment may be one of the following: note, 16th note, breath or one of the types of single-note or multi-note ornaments. The note frequency is determined automatically by the tool based on estimated pitch towards the end of the segment. An example excerpt, corresponding to the audio signal shown in Figure 3.2, from the annotation file is depicted in Table 3.1. The passage starts with a *long roll* consisting of the sequence starting with the root note *lngroll_nt*, cut *lngroll_ct*, back to the root *lngroll_nt*, strike *lngroll_str* and back to the root note *lngroll_nt*.

Later tunes were annotated using the Tony software (Mauch et al., 2015) as shown in Figure 3.3. Tony is designed for manual annotation of audio files and tests showed that these tasks took less time. Furthermore, automatic pitch estimation was more accurate, using PYIN (Mauch and Dixon, 2014), and did not result in as many doubling errors as found in YIN with Sonic Visualiser. The bottom of the screen shows the waveform of the source audio file and the light blue horizontal blocks in the centre of the screen depict the note onset and offset with frequencies taken from the piano roll on the left hand side. The darker line running through the centre of each block is the F_0 frequency estimates. In this example, the F_0 is accurate apart from the fifth note, a cut, which was not detected but subsequently manually corrected.

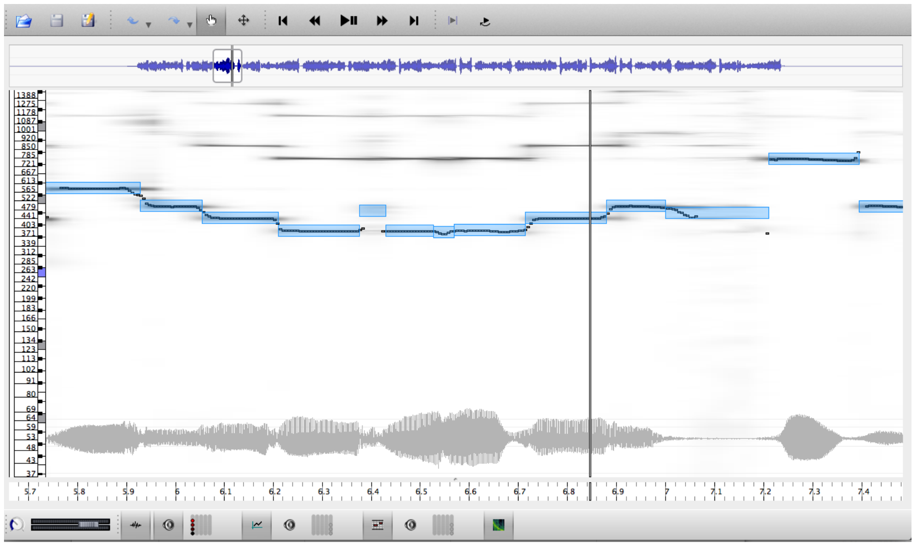


Figure 3.3: An example of a screenshot from Tony analysis and annotation software, depicting waveform (bottom) and spectrogram with indicated manually annotated notes (light blue horizontal blocks). Tune: McGivney's Fancy by Catherine McEvoy Tune No.30 in Table 3.2.

Onset(s)	Offset(s)	Duration(s)	Segment Type	Note	Freq(Hz)
38.272	38.402	0.130	lngRoll_nt	A4	433.468
38.402	38.440	0.038	lngRoll_ct	C5	510.187
38.451	38.496	0.045	lngRoll_nt	A4	436.754
38.498	38.542	0.044	lngRoll_str	A4	419.867
38.549	38.706	0.157	lngRoll_nt	A4	437.322
38.718	39.053	0.335	NOTE	F#5	725.978
39.053	39.204	0.151	NOTE	D5	586.138
39.204	39.337	0.133	NOTE	F#5	719.640
39.337	39.380	0.043	ct	F#5	754.629
39.380	39.543	0.163	NOTE	E5	648.898
39.545	39.704	0.159	NOTE	D5	583.062
39.712	39.867	0.155	NOTE	C5	515.701

Table 3.1: An example of metadata created from manual annotation of a tune as illustrated in Figure 3.2, Shaskeen by Grey Larsen (38.37–39.70s).

Table 3.2: Players, tune title and type, recording source and key

No.	Player	Tune Title	Recording	Type	Key
1	Bradley, Harry	Ah Surely	The First of May	Reel	Gmaj
2	Bradley, Harry	Ah Surely	The First of May	Reel	Gmaj
3	Bradley, Harry	Ah Surely	The First of May	Reel	Gmaj
4	Bradley, Harry	The Flowers Of Red Hill	The First of May	Reel	Ador
5	Bradley, Harry	The Flowers Of Red Hill	The First of May	Reel	Ador
6	Bradley, Harry	The Flowers Of Red Hill	The First of May	Reel	Ador
7	Bradley, Harry	The Gallant Boys Of Tipperary	The First of May	Jig	Dmaj
8	Bradley, Harry	The Whinny Hills Of Leitrim	The First of May	SlipJig	Dmaj
9	Bradley, Harry	The Dancer At The Fair	The First of May	Hornpipe	Gmaj
10	Bradley, Harry	The Dancer At The Fair	The First of May	Hornpipe	Gmaj
11	Bradley, Harry	Fishers Hornpipe	The First of May	Hornpipe	Gmaj
12	Bradley, Harry	Fishers Hornpipe	The First of May	Hornpipe	Gmaj
13	Bradley, Harry	Happy To Meet Sorry To Part	The First of May	Jig	Gmaj
14	Bradley, Harry	The Rakes Of Kildare	The First of May	Jig	Ador
15	Bradley, Harry	The Hare's Paw	The First of May	Reel	Gmaj
16	Bradley, Harry	The Hare's Paw	The First of May	Reel	Gmaj
17	Flaherty, Bernard	Down The Broom	Flute Players of Roscommon Vol 1	Reel	Ador
18	Flaherty, Bernard	The Gatehouse Maid	Flute Players of Roscommon Vol 1	Reel	Gmaj
19	Kelly, John	Gerry's Beaver Hat	Flute Players of Roscommon Vol 1	Hornpipe	Dmaj
20	Kelly, John	Adam And Eve	Flute Players of Roscommon Vol 1	Jig	Gmaj
21	McDermott, Josie	The Kerry Man	Darby's Farewell	Reel	Cmaj
22	McDermott, Josie	The Pigeon on the Gate	Darby's Farewell	Reel	Edor
23	McDermott, Josie	The Bush Hornpipe	Darby's Farewell	Hornpipe	Ador
24	McDermott, Josie	Dunphy's Hornpipe	Darby's Farewell	Hornpipe	Gmaj
25	McDermott, Josie	Dominic's Farewell to Cashel	Darby's Farewell	Jig	Gmaj
26	McDermott, Josie	Trip to the Cottage	Darby's Farewell	Jig	Gmaj
27	McEvoy, Catherine	Crehan's Kitchen	Flute Players of Roscommon Vol 1	Reel	Dmaj
28	McEvoy, Catherine	The Sand Mount	Flute Players of Roscommon Vol 1	Reel	Ador
29	McEvoy, Catherine	Mulvihill's	Flute Players of Roscommon Vol 1	Reel	Gmaj
30	McEvoy, Catherine	McGivney's Fancy	Traditional Flute Playing i	Reel	Edor
31	Molloy, Matt	The Bush In Bloom	Heathery Breeze	Reel	Gmaj
32	Molloy, Matt	Drowsy Maggie	Heathery Breeze	Reel	Edor
33	Molloy, Matt	The Hare In The Heather	Heathery Breeze	Reel	Edor
34	Molloy, Matt	The Humours of Ballyloughlin	Matt Molloy	Jig	Dmix
35	Molloy, Matt	The Gold Ring	Matt Molloy	Jig	Gmaj
36	Molloy, Matt	The Crib Of Perches	Shadows on Stone	Reel	Dmix
37	Molloy, Matt	The Mason's Apron	Shadows on Stone	Reel	Gmaj
38	O'Grada, Conal	Mickey Duggan's Polka No.1	Cnoc Bui	Polka	Dmaj
39	O'Grada, Conal	Mickey Duggan's Polka No.2	Cnoc Bui	Polka	Dmaj
40	O'Grada, Conal	Cus Teahan's	Cnoc Bui	Reel	Dmaj
41	O'Grada, Conal	Jim Donoghue's	Cnoc Bui	Reel	Dmaj
42	O'Grada, Conal	The Edenderry Reel	Cnoc Bui	Reel	Gmaj
43	O'Grada, Conal	The Church Street Polka	Cnoc Bui	Polka	Gmaj
44	O'Grada, Conal	The Church Street Polka	Cnoc Bui	Polka	Gmaj

45	O'Grada, Conal	The Church Street Polka	Cnoc Bui	Polka	Gmaj
46	O'Grada, Conal	The Happy Polka	Cnoc Bui	Polka	Dmaj
47	O'Grada, Conal	The Happy Polka	Cnoc Bui	Polka	Dmaj
48	O'Grada, Conal	The Happy Polka	Cnoc Bui	Polka	Dmaj
49	O'Grada, Conal	The Fisherman's Lilt	CnocBui	Reel	Dmaj
50	O'Grada, Conal	The Fisherman's Lilt	CnocBui	Reel	Dmaj
51	O'Grada, Conal	The Fisherman's Lilt	CnocBui	Reel	Dmaj
52	O'Grada, Conal	The Caucus Reel	CnocBui	Reel	Gmaj
53	O'Grada, Conal	The Caucus Reel	CnocBui	Reel	Gmaj
54	O'Grada, Conal	Muing Phliuch Jig	Cnoc Bui	Jig	Dmaj
55	O'Grada, Conal	GreenMountain	Cnoc Bui	Reel	Dmaj
56	O'Grada, Conal	GreenMountain	Cnoc Bui	Reel	Dmaj
57	O'Grada, Conal	The Rookery	Cnoc Bui	Reel	Dmix
58	O'Grada, Conal	Maurice O'Keeffe's	Cnoc Bui	Polka	Dmaj
59	O'Grada, Conal	John Walshes	Cnoc Bui	Polka	Dmaj
60	O'Grada, Conal	The Old Copperplate	Cnoc Bui	Reel	Ador
61	O'Grada, Conal	The Old Bush	Cnoc Bui	Reel	Dmix
62	Tansey, Seamus	The Flax In Bloom	Field Recordings	Reel	Dmaj
63	Tansey, Seamus	Blackberry Blossom	Field Recordings	Reel	Gmaj
64	Tansey, Seamus	The Maid Behind The Bar	Field Recordings	Reel	Dmaj
65	Tansey, Seamus	Cornel Fraizer	Field Recordings	Reel	Gmaj
66	Tubridy, Michael	The Humours Of Derrykissanne	The Eagle's Whistle	SlipJig	Dmaj
67	Tubridy, Michael	The Humours Of Derrykissanne	The Eagle's Whistle	SlipJig	Dmaj
68	Tubridy, Michael	The Humours Of Derrykissanne	The Eagle's Whistle	SlipJig	Dmaj
69	Tubridy, Michael	The Campbells Are Coming	The Eagle's Whistle	SlipJig	Gmaj
70	Tubridy, Michael	The Campbells Are Coming	The Eagle's Whistle	SlipJig	Gmaj
71	Tubridy, Michael	The Campbells Are Coming	The Eagle's Whistle	SlipJig	Gmaj
72	Tubridy, Michael	The Hawthorn	The Eagle's Whistle	SlipJig	Gmaj
73	Tubridy, Michael	The Hawthorn	The Eagle's Whistle	SlipJig	Gmaj
74	Tubridy, Michael	The Hawthorn	The Eagle's Whistle	SlipJig	Gmaj
75	Tubridy, Michael	The Ashplant	The Eagle's Whistle	Reel	Edor
76	Tubridy, Michael	For The Sake Of Old Decency	The Eagle's Whistle	Reel	Gmaj
77	Wynne, John	The Girl In The Big House	Flute Players of Roscommon Vol 1	Jig	Dmix
78	Wynne, John	The Killavil Jig	Flute Players of Roscommon Vol 1	Jig	Edor
79	Wynne, John	The Maid On The Green	Flute Players of Roscommon Vol 1	Jig	Gmaj
80	Larsen, Grey	The Lonesome Jig	The Essential Guide to Flute and Tin Whistle	Jig	Dmaj
81	Larsen, Grey	study5	The Essential Guide to Flute and Tin Whistle	Reel	
82	Larsen, Grey	study6	The Essential Guide to Flute and Tin Whistle	Reel	
83	Larsen, Grey	study11	The Essential Guide to Flute and Tin Whistle	Reel	
84	Larsen, Grey	study17	The Essential Guide to Flute and Tin Whistle	Jig	
85	Larsen, Grey	study22	The Essential Guide to Flute and Tin Whistle	Jig	
86	Larsen, Grey	Tom Billy's Jig	The Essential Guide to Flute and Tin Whistle	Jig	Ador
87	Larsen, Grey	The Frost Is All Over	The Essential Guide to Flute and Tin Whistle	Jig	Dmaj
88	Larsen, Grey	The Humours Of Ballyloughlin	The Essential Guide to Flute and Tin Whistle	Jig	Dmix
89	Larsen, Grey	The Rose In The Heather	The Essential Guide to Flute and Tin Whistle	Jig	Dmaj
90	Larsen, Grey	Scotsman Over The Border	The Essential Guide to Flute and Tin Whistle	Jig	Dmaj

91	Larsen, Grey	A Fig For A Kiss	The Essential Guide to Flute and Tin Whistle	SlipJig	Edor
92	Larsen, Grey	Hardiman The Fiddler	The Essential Guide to Flute and Tin Whistle	SlipJig	Ador
93	Larsen, Grey	The Whinny Hills Of Leitrim	The Essential Guide to Flute and Tin Whistle	SlipJig	Dmaj
94	Larsen, Grey	Roaring Mary	The Essential Guide to Flute and Tin Whistle	Reel	Dmaj
95	Larsen, Grey	The Drunken Landlady	The Essential Guide to Flute and Tin Whistle	Reel	Edor
96	Larsen, Grey	The Lady On The Island	The Essential Guide to Flute and Tin Whistle	Reel	Dmaj
97	Larsen, Grey	The Mountain Road	The Essential Guide to Flute and Tin Whistle	Reel	Dmaj
98	Larsen, Grey	The Shaskeen	The Essential Guide to Flute and Tin Whistle	Reel	Gmaj
99	Larsen, Grey	Maids Of Ardagh	The Essential Guide to Flute and Tin Whistle	Polka	Amix

Table 3.3: Use of data in published papers

No.	Player	Tune Title	Kelleher	FMA14	ISMIR14	FMA15	FMA16	FMA17/18
1	Bradley, Harry	Ah Surely				x	x	x
2	Bradley, Harry	Ah Surely					x	x
3	Bradley, Harry	Ah Surely					x	x
4	Bradley, Harry	The Flowers Of Red Hill				x	x	x
5	Bradley, Harry	The Flowers Of Red Hill					x	x
6	Bradley, Harry	The Flowers Of Red Hill					x	x
7	Bradley, Harry	The Gallant Boys Of Tipperary					x	x
8	Bradley, Harry	The Whinny Hills Of Leitrim					x	x
9	Bradley, Harry	The Dancer At The Fair					x	x
10	Bradley, Harry	The Dancer At The Fair					x	x
11	Bradley, Harry	Fishers Hornpipe					x	x
12	Bradley, Harry	Fishers Hornpipe					x	x
13	Bradley, Harry	Happy To Meet Sorry To Part				x	x	x
14	Bradley, Harry	The Rakes Of Kildare					x	x
15	Bradley, Harry	The Hare's Paw				x	x	x
16	Bradley, Harry	The Hare's Paw					x	x
17	Flaherty, Bernard	Down The Broom					x	x
18	Flaherty, Bernard	The Gatehouse Maid					x	x
19	Kelly, John	Gerry's Beaver Hat					x	x
20	Kelly, John	Adam And Eve					x	x
21	McDermott, Josie	The Kerry Man					x	x
22	McDermott, Josie	The Pigeon on the Gate					x	x
23	McDermott, Josie	The Bush Hornpipe					x	x
24	McDermott, Josie	Dunphy's Hornpipe					x	x
25	McDermott, Josie	Dominic's Farewell to Cashel					x	x
26	McDermott, Josie	Trip to the Cottage					x	x
27	McEvoy, Catherine	Crehan's Kitchen					x	x
28	McEvoy, Catherine	The Sand Mount					x	x
29	McEvoy, Catherine	Mulvihill's					x	x
30	McEvoy, Catherine	McGivney's Fancy					x	x
31	Molloy, Matt	The Bush In Bloom				x	x	x
32	Molloy, Matt	Drowsy Maggie				x	x	x
33	Molloy, Matt	The Hare In The Heather				x	x	x
34	Molloy, Matt	The Humours of Ballyloughlin					x	x
35	Molloy, Matt	The Gold Ring					x	x
36	Molloy, Matt	The Crib Of Perches				x	x	x
37	Molloy, Matt	The Mason's Apron					x	x
38	O'Grada, Conal	Mickey Duggan's Polka No.1					x	x
39	O'Grada, Conal	Mickey Duggan's Polka No.2					x	x
40	O'Grada, Conal	Cus Teahan's					x	x
41	O'Grada, Conal	Jim Donoghue's					x	x
42	O'Grada, Conal	The Edenderry Reel					x	x
43	O'Grada, Conal	The Church Street Polka					x	x
44	O'Grada, Conal	The Church Street Polka					x	x

45	O'Grada, Conal	The Church Street Polka					x	x
46	O'Grada, Conal	The Happy Polka					x	x
47	O'Grada, Conal	The Happy Polka					x	x
48	O'Grada, Conal	The Happy Polka					x	x
49	O'Grada, Conal	The Fisherman's Lilt					x	x
50	O'Grada, Conal	The Fisherman's Lilt					x	x
51	O'Grada, Conal	The Fisherman's Lilt					x	x
52	O'Grada, Conal	The Caucus Reel					x	x
53	O'Grada, Conal	The Caucus Reel					x	x
54	O'Grada, Conal	Muing Phliuch Jig				x	x	x
55	O'Grada, Conal	GreenMountain				x	x	x
56	O'Grada, Conal	GreenMountain					x	x
57	O'Grada, Conal	The Rookery					x	x
58	O'Grada, Conal	Maurice O'Keeffe's				x	x	x
59	O'Grada, Conal	John Walshes					x	x
60	O'Grada, Conal	The Old Copperplate				x	x	x
61	O'Grada, Conal	The Old Bush					x	x
62	Tansey, Seamus	The Flax In Bloom				x	x	x
63	Tansey, Seamus	Blackberry Blossom				x	x	x
64	Tansey, Seamus	The Maid Behind The Bar				x	x	x
65	Tansey, Seamus	Cornel Fraizer				x	x	x
66	Tubridy, Michael	The Humours Of Derrykissanne				x	x	x
67	Tubridy, Michael	The Humours Of Derrykissanne					x	x
68	Tubridy, Michael	The Humours Of Derrykissanne					x	x
69	Tubridy, Michael	The Campbells Are Coming				x	x	x
70	Tubridy, Michael	The Campbells Are Coming					x	x
71	Tubridy, Michael	The Campbells Are Coming					x	x
72	Tubridy, Michael	The Hawthorn					x	x
73	Tubridy, Michael	The Hawthorn					x	x
74	Tubridy, Michael	The Hawthorn					x	x
75	Tubridy, Michael	The Ashplant				x	x	x
76	Tubridy, Michael	For The Sake Of Old Decency				x	x	x
77	Wynne, John	The Girl In The Big House					x	x
78	Wynne, John	The Killavil Jig					x	x
79	Wynne, John	The Maid On The Green					x	x
80	Larsen, Grey	The Lonesome Jig	x	x	x			
81	Larsen, Grey	study5	x	x	x			
82	Larsen, Grey	study6	x	x	x			
83	Larsen, Grey	study11	x	x	x			
84	Larsen, Grey	study17	x	x	x			
85	Larsen, Grey	study22	x	x	x			
86	Larsen, Grey	Tom Billy's Jig						
87	Larsen, Grey	The Frost Is All Over						
88	Larsen, Grey	The Humours Of Ballyloughlin						
89	Larsen, Grey	The Rose In The Heather						
90	Larsen, Grey	Scotsman Over The Border						

91	Larsen, Grey	A Fig For A Kiss						
92	Larsen, Grey	Hardiman The Fiddler	x	x	x			
93	Larsen, Grey	The Whinny Hills Of Leitrim	x	x	x			
94	Larsen, Grey	Roaring Mary						
95	Larsen, Grey	The Drunken Landlady						
96	Larsen, Grey	The Lady On The Island	x	x	x			
97	Larsen, Grey	The Mountain Road						
98	Larsen, Grey	The Shaskeen						
99	Larsen, Grey	Maids Of Ardagh	x	x	x			

Table 3.4: Recordings and transcription

No.	Player	Tune Title	Software	BPM	Key	Tuning A=Hz	Actual Key	Flute	D Freq	Transp.
1	Bradley, Harry	Ah Surely	SV	109	Gmaj	A = 440Hz	Bbmaj	F		Bbmaj
2	Bradley, Harry	Ah Surely	T	113	Gmaj	A = 440Hz	Bbmaj	F		Bbmaj
3	Bradley, Harry	Ah Surely	T	114	Gmaj	A = 440Hz	Bbmaj	F		Bbmaj
4	Bradley, Harry	The Flowers Of Red Hill	SV	116	Ador	A = 440Hz	Cdor	F		Cdor
5	Bradley, Harry	The Flowers Of Red Hill	SV	116	Ador	A = 440Hz	Cdor	F		Cdor
6	Bradley, Harry	The Flowers Of Red Hill	T	115	Ador	A = 440Hz	Cdor	F		Cdor
7	Bradley, Harry	The Gallant Boys Of Tipperary	SV	141	Dmaj	A = 440Hz	Fmaj	F		Fmaj
8	Bradley, Harry	The Whinny Hills Of Leitrim	T	138	Dmaj	A = 440Hz	Fmaj	F	349.23	Fmaj
9	Bradley, Harry	The Dancer At The Fair	SV	88	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
10	Bradley, Harry	The Dancer At The Fair	T	92	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
11	Bradley, Harry	Fishers Hornpipe	T	94	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
12	Bradley, Harry	Fishers Hornpipe	T	95	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
13	Bradley, Harry	Happy To Meet Sorry To Part	SV	125	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
14	Bradley, Harry	The Rakes Of Kildare	T	128	Ador	A = 440Hz	Bbdor	Eb	311.13	Bbdor
15	Bradley, Harry	The Hare's Paw	SV	105	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
16	Bradley, Harry	The Hare's Paw	T	107	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
17	Flaherty, Bernard	Down The Broom	SV	110	Ador	A = 440Hz	Ador	D	293.66	
18	Flaherty, Bernard	The Gatehouse Maid	SV	110	Ador	A = 440Hz	Ador	D	293.66	
19	Kelly, John	Gerry's Beaver Hat	SV	125	Dmaj	A = 440Hz	Dmaj	D	293.66	
20	Kelly, John	Adam And Eve	SV	128	Gmaj	A = 440Hz	Gmaj	D	293.66	
21	McDermott, Josie	The Kerry Man	T	105	Edor	A=415Hz	Edor	D	278	
22	McDermott, Josie	The Pigeon on the Gate	T	108	Edor	A=415Hz	Edor	D	278	
23	McDermott, Josie	The Bush Hornpipe	T	88	Ador	A=415Hz	Ador	D	278	
24	McDermott, Josie	Dunphy's Hornpipe	T	89	Gmaj	A=415Hz	Gmaj	D	278	
25	McDermott, Josie	Dominic's Farewell to Cashel	T	113	Gmaj	A=415Hz	Gmaj	D	278	
26	McDermott, Josie	Trip to the Cottage	T	123	Gmaj	A=415Hz	Gmaj	D	278	
27	McEvoy, Catherine	Crehan's Kitchen	SV	101	Dmaj	A = 440Hz	Dmaj	D	293.66	
28	McEvoy, Catherine	The Sand Mount	SV	106	Ador	A = 440Hz	Ador	D	293.66	
29	McEvoy, Catherine	Mulvihill's	SV	107	Gmaj	A = 440Hz	Gmaj	D	293.66	
30	McEvoy, Catherine	McGivney's Fancy	T	89	Edor	A = 440Hz	Edor	D	293.66	
31	Molloy, Matt	The Bush In Bloom	SV	118	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
32	Molloy, Matt	Drowsy Maggie	SV	76	Edor	A = 440Hz	Dbdor	Bb	233.08	Dbdor
33	Molloy, Matt	The Hare In The Heather	SV	90	Edor	A = 440Hz	Fdor	Eb	311.13	Fdor
34	Molloy, Matt	The Humours of Ballyloughlin	SV	101	Dmaj	A = 440Hz	Dmaj	D	293.66	
35	Molloy, Matt	The Gold Ring	SV	90	Gmaj	A = 440Hz	Gmaj	D	293.66	
36	Molloy, Matt	The Crib Of Perches	T	122	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
37	Molloy, Matt	The Mason's Apron	T	120	Dmix	A = 440Hz	Ebmix	Eb	311.13	Ebmix
38	O'Grada, Conal	Mickey Duggan's Polka No.1	SV	138	Dmaj	A = 440Hz	Dmaj	D	293.66	
39	O'Grada, Conal	Mickey Duggan's Polka No.2	SV	138	Dmaj	A = 440Hz	Dmaj	D	293.66	
40	O'Grada, Conal	Cus Teahan's	T	105	Gmaj	A = 440Hz	Gmaj	D	293.66	
41	O'Grada, Conal	Jim Donoghue's	T	110	Dmaj	A = 440Hz	Dmaj	D	293.66	
42	O'Grada, Conal	The Edenderry Reel	T	112	Gmaj	A = 440Hz	Gmaj	D	293.66	
43	O'Grada, Conal	The Church Street Polka	SV	135	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
44	O'Grada, Conal	The Church Street Polka	SV	134	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
45	O'Grada, Conal	The Church Street Polka	SV	133	Gmaj	A = 440Hz	Abmaj	Eb	311.13	Abmaj
46	O'Grada, Conal	The Happy Polka	SV	133	Dmaj	A = 440Hz	Ebmaj	Eb	311.13	Ebmaj
47	O'Grada, Conal	The Happy Polka	SV	134	Dmaj	A = 440Hz	Ebmaj	Eb	311.13	Ebmaj
48	O'Grada, Conal	The Happy Polka	SV	134	Dmaj	A = 440Hz	Ebmaj	Eb	311.13	Ebmaj
49	O'Grada, Conal	The Fisherman's Lilt	T	109	Dmaj	A = 440Hz	Dmaj	D	293.66	
50	O'Grada, Conal	The Fisherman's Lilt	T	110	Dmaj	A = 440Hz	Dmaj	D	293.66	
51	O'Grada, Conal	The Fisherman's Lilt	T	110	Dmaj	A = 440Hz	Dmaj	D	293.66	
52	O'Grada, Conal	The Caucus Reel	T	112	Gmaj	A = 440Hz	Gmaj	D	293.66	
53	O'Grada, Conal	The Caucus Reel	T	113	Gmaj	A = 440Hz	Gmaj	D	293.66	
54	O'Grada, Conal	Muing Phliuch Jig	SV	117	Dmaj	A = 440Hz	Dmaj	D	293.66	
55	O'Grada, Conal	GreenMountain	SV	104	Dmaj	A = 440Hz	Dmaj	D	293.66	
56	O'Grada, Conal	GreenMountain	T	112	Dmaj	A = 440Hz	Dmaj	D	293.66	
57	O'Grada, Conal	The Rookery	T	113	Gmaj	A = 440Hz	Gmaj	D	293.66	
58	O'Grada, Conal	Maurice O'Keeffe's	SV	142	Gmaj	A = 440Hz	Gmaj	D	293.66	
59	O'Grada, Conal	John Walshes	T	136	Dmaj	A = 440Hz	Dmaj	D	293.66	

60	O'Grada, Conal	The Old Copperplate	SV	112	Ador	A = 440Hz	Ador	D	293.66	
61	O'Grada, Conal	The Old Bush	T	113	Dmix	A = 440Hz	Dmix	D	293.66	
62	Tansey, Seamus	The Flax In Bloom	SV	116	Gmaj	A = 440Hz	Gmaj	D	293.66	
63	Tansey, Seamus	Blackberry Blossom	SV	116	Dmaj	A = 440Hz	Dmaj	D	293.66	
64	Tansey, Seamus	The Maid Behind The Bar	SV	116	Dmaj	A = 440Hz	Dmaj	D	293.66	
65	Tansey, Seamus	Cornel Fraizer	SV	116	Gmaj	A = 440Hz	Gmaj	D	293.66	
66	Tubridy, Michael	The Humours Of Derrykissanne	SV	131	Dmaj	A = 440Hz	Gmaj	D	293.66	
67	Tubridy, Michael	The Humours Of Derrykissanne	SV	132	Dmaj	A = 440Hz	Gmaj	D	293.66	
68	Tubridy, Michael	The Humours Of Derrykissanne	SV	133	Dmaj	A = 440Hz	Gmaj	D	293.66	
69	Tubridy, Michael	The Campbells Are Coming	SV	134	Gmaj	A = 440Hz	Gmaj	D	293.66	
70	Tubridy, Michael	The Campbells Are Coming	SV	132	Gmaj	A = 440Hz	Gmaj	D	293.66	
71	Tubridy, Michael	The Campbells Are Coming	SV	132	Gmaj	A = 440Hz	Gmaj	D	293.66	
72	Tubridy, Michael	The Hawthorn	SV	132	Gmaj	A = 440Hz	Gmaj	D	293.66	
73	Tubridy, Michael	The Hawthorn	SV	132	Gmaj	A = 440Hz	Gmaj	D	293.66	
74	Tubridy, Michael	The Hawthorn	SV	132	Gmaj	A = 440Hz	Gmaj	D	293.66	
75	Tubridy, Michael	The Ashplant	SV	110	Edor	A = 440Hz	Gmaj	D	293.66	
76	Tubridy, Michael	For The Sake Of Old Decency	SV	117	Gmaj	A = 440Hz	Gmaj	D	293.66	
77	Wynne, John	The Girl In The Big House	SV	125	Dmix	A = 440Hz	Dmix	D	293.66	
78	Wynne, John	The Killavil Jig	SV	131	Edor	A = 440Hz	Edor	D	293.66	
79	Wynne, John	The Maid On The Green	SV	131	Gmaj	A = 440Hz	Gmaj	D	293.66	
80	Larsen, Grey	The Lonesome Jig	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
81	Larsen, Grey	study5	SV			A = 440Hz		D	293.66	
82	Larsen, Grey	study6	SV			A = 440Hz		D	293.66	
83	Larsen, Grey	study11	SV			A = 440Hz		D	293.66	
84	Larsen, Grey	study17	SV			A = 440Hz		D	293.66	
85	Larsen, Grey	study22	SV			A = 440Hz		D	293.66	
86	Larsen, Grey	Tom Billy's Jig	SV		Ador	A = 440Hz	Ador	D	293.66	
87	Larsen, Grey	The Frost Is All Over	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
88	Larsen, Grey	The Humours Of Ballyloughlin	SV		Dmix	A = 440Hz	Dmix	D	293.66	
89	Larsen, Grey	The Rose In The Heather	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
90	Larsen, Grey	Scotsman Over The Border	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
91	Larsen, Grey	A Fig For A Kiss	SV		Edor	A = 440Hz	Edor	D	293.66	
92	Larsen, Grey	Hardiman The Fiddler	SV		Ador	A = 440Hz	Ador	D	293.66	
93	Larsen, Grey	The Whinny Hills Of Leitrim	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
94	Larsen, Grey	Roaring Mary	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
95	Larsen, Grey	The Drunken Landlady	SV		Edor	A = 440Hz	Edor	D	293.66	
96	Larsen, Grey	The Lady On The Island	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
97	Larsen, Grey	The Mountain Road	SV		Dmaj	A = 440Hz	Dmaj	D	293.66	
98	Larsen, Grey	The Shaskeen	SV		Gmaj	A = 440Hz	Gmaj	D	293.66	
99	Larsen, Grey	Maids Of Ardagh	SV		Dmaj		Dmaj	D	293.66	

3.3 ITM-Flute-Style6

The *ITM-Flute-Style6* dataset consists of 28 recordings by each of 6 players (168 total). All tracks include only flute recordings with no accompaniment. The set covers a range of melodies or *tunes* that are common in the ITM community. The average duration of all tracks is approximately 43 seconds. The total duration of the dataset is 2 hours.

This dataset differs from the existing ITM flute datasets in that it targets multiple player traits and playing contexts that can substantiate further player style research. The presented tune types (i.e., *reels*, *jigs* and *hornpipes*) correspond to an informal online survey conducted among a group of experienced ITM players. The tune names can be seen in Table 3.5, where the last two represent individually chosen *wild* tracks by each player. The tune type category covers the three most popular tune types in ITM. Five categories are used to structure the dataset by: 1) player, 2) tune name, 3) tune type, 4) timed (*i.e.,* played to metronome) and 5) first or second repeat. All recorded flute players have substantial experience in playing and performing in the style of ITM. The timing category segregates the tracks into timed using a metronome, and untimed. All melodies were recorded twice in segue (first and second repeat) with and without metronome except wild tracks, which were only recorded without metronome.

The recordings were collected as 16-bit/44.1kHz WAV files using a Thomann MM-1 measurement microphone connected to an Audient ID14 audio interface, as shown in Figure 3.4. The microphone was positioned above the middle of the flute in order to minimise wind noise caused by blowing. Metadata accompanying the recordings can be found in Appendix B.

3.4 Chapter summary

This chapter has discussed the collection of two datasets of solo Irish traditional flute recordings, including the *ITM-Flute-99* dataset, comprised of 99 solo flute recordings of between 16 and 81 seconds in length spanning over 11 players and 50 years, and the *ITM-Flute-Style6* dataset consisting of 28 recordings by each of 6 players (168 total), with a total duration of approximately 2 hours.

These datasets are important because they are representative of a number of playing styles playing different melodies as well as a number of players' approach to the same melodies. The datasets allow subsequent analysis to be undertaken, enabling a greater understanding of traditional Irish flute playing style. The following chapter presents computational methods for the analysis of stylistic features, focusing on methods for identifying both timbral and temporal features.

No.	Tune Title	Type	Scale	Ends on
1	Maids of Mount Cisco	Reel	G	Ray
2	The Banshee	Reel	G	Soh
3	Cooley's Reel	Reel	G	Lah
4	Banish Misfortune	Jig	G	Doh
5	Morrison's Jig	Jig	D	Ray
6	The Home Ruler	Hornpipe	D	Doh
7	Players choice 1	Wild	n/a	n/a
8	Players choice 2	Wild	n/a	n/a

Table 3.5: Corpus recorded by all players detailing tune type, scale and ending note.

Figure 3.4: Recording of flute player for *ITM-Flute-Style6* dataset

Chapter 4

Computational methods for stylistic analysis

The previous chapters have concentrated on the production of ITM on the flute (Chapter 2) and the collection of flute recordings and metadata for analysis of stylistic features (Chapter 3) . This chapter focuses on the computational techniques used to analyse traditional flute playing. Timbre, or tonality, and the rhythmic playing of notes and ornaments are important factors in determining a traditional flute player's style. In order to automatically evaluate a melody played on a flute, the signal can be analysed in terms of pitch, timbre and rhythm. Each contributes important information to an overall investigation where individual notes and ornaments can be examined. These are important steps in underpinning a musicological investigation of traditional flute music and it is expected that automated analysis will allow a greater understanding of individual playing style.

A range of musical instruments playing the same note or pitch can be differentiated by timbre and amplitude envelope (Helmholtz and Ellis, 1875). Dynamics, or control of amplitude, were not considered independently in these computational methods because many players rely on a smooth or non-dynamic style of playing. The simple system flute also has a small dynamic range in comparison with later designs Tanner (2018). The use of convolutional neural networks trained on graphical images of spectra does, however, lead to a dynamic component being part of the classification process (Qu et al., 2016).

The pitch of the note is represented by a fundamental frequency F_0, and multiples of this frequency also present in the played note are known as partials or harmonics. The amplitude envelope can be divided into attack, steady-state and decay sections. The attack is a transient section from commencement of the note until the partials remain steady, continuing for the rest of the note. The decay occurs when the player stops but the sound continues. As well as being key indicators of different types of musical instruments, flute players can be individuated by the timbre they produce as well as manipulation of the amplitude envelope. Section 4.1 contains an overview of timbral analysis of pitched musical sounds used to identify the fundamental frequency of the note being played along with other harmonic energy. A review of approaches for the spectral analysis of musical events and use of the steady-state section of the amplitude envelope is also presented.

The choice of notes and ornaments used by a flute player to interpret a traditional melody is intrinsic to their playing style. The detection of significant musical events, known as onset detection, allows for the automatic segmentation of a melody into component parts. The main steps of onset detection are presented in Section 4.2. Section 4.2.1 covers strategies for optimising the input signal and Section 4.2.2 presents methods of emphasising signal features that contribute towards event detection. Section 4.2.4 discusses machine listening; the use of signal processing and machine learning to extract useful information from sound (*Machine Listening Lab* 2017) and in particular how machine learning, the use of computers to make data-driven decisions, can be utilised for onset detection. Section 4.2.3 considers peak picking, methods for selecting onsets from the reduced data. Finally, Section 4.3 presents examples of key techniques used in the analysis of flute playing style.

4.1 Timbral features

Timbre, or tonal quality, is of central importance to the playing style of many traditional musicians. It is one of the stylistic components identified by Keegan (2010) as a key technique used by Irish traditional musicians. Schouten (1968) encapsulated many of the features found in flute playing by defining a set of acoustic parameters: The range between tonal and noiselike character; the spectral envelope; the time envelope in terms of rise, duration and decay; the changes both of spectral envelope and fundamental frequency; and the prefix, an onset of a sound quite dissimilar to the ensuing lasting vibration. These parameters illustrate the importance of timbral and onset detection with regard to music analysis and have formed a central core for research into musical style.

4.1.1 Fourier transform

Pitched musical sounds that we hear, with the exception of sinusoidal tones, contain a fundamental frequency F_0 and a number of overtones, also known as partials. Partials that are integer multiples of F_0 are known as harmonics. In order to calculate the partials or harmonic components of a sound, the discrete Fourier transform (DFT) is used to transform a time domain signal x containing N samples into a frequency domain signal X by decomposing the signal into a number of sine and cosine components of different frequencies.

Two types of spectral analysis, known as short-time and long-term average spectra, are commonly used in speech and singing analysis (Howard and Murphy, 2007). These approaches are also used in music analysis, particularly where there are longer notes with a stable central section between attack and release transients, as produced by woodwind or bowed instruments (Fletcher and Rossing, 2013).

The studies discussed in Section 4.1 led to the understanding that natural sounds are by nature non-stationary and that their properties, particularly timbral, vary over time. As the use of the DFT does not reflect these changes, the Short-Time Fourier Transform (STFT) is used.

The STFT is used to segment the signal into a number of frames and the Discrete Fourier Transform (DFT) is computed at each frame. It is used to calculate the frequency content of specific regions of a longer signal by computing the DFT for each region. Each frame of audio is computed using a window function where the effect of out of phase signal components at the start and end of the frame are minimised. Frequency information at different times is calculated by repeatedly shifting the window by a predetermined time and computing a DFT at each instance (Müller, 2015).

The value of each frequency bin k of spectral frame m of signal X is obtained from input signal x, using a window function w of length L, a hop size in samples of δ and a sample index n. M is the number of STFT frames and j corresponds to the imaginary unit and X_m is the mth frame's spectral vector containing magnitude and phase components:

$$X_k(m) = \sum_{n=0}^{L-1} x(n + m\delta)w(n)e^{-j\frac{2\pi kn}{N}}. \tag{4.1}$$

A magnitude spectrogram S_k can be computed using the absolute value of X_k.

4.1.2 Long-term average spectrum (LTAS)

The long-term average spectrum (LTAS) is used to view spectral information averaged over time (Jansson, 1976). The LTAS is achieved through:

$$LTAS = \frac{1}{M} \sum_{m=0}^{M-1} X_m. \tag{4.2}$$

It has been used in a number of studies on speech analysis (White, 2001; Leino, 2009; Sergeant and Welch, 2009) and singing (Boersma and Kovacic, 2006). It is used to classify voices in several ways, showing differences between age, gender, and musical training (Master et al., 2006).

LTAS analysis can also be used to obtain spectral information about long musical notes. Furthermore, it is recommended by Fletcher and Rossing (2013) for analysis of bowed instruments, either in an anechoic room if directional sound is required, or in a reverberation room if an overall sound power is needed.

4.1.3 Mel-frequency cepstral coefficients (MFCC)

The mel-frequency cepstrum is a representation of the short-time power spectrum of a sound. It is computed by using the linear cosine transform of a logarithmic power spectrum based on the mel scale (Mermelstein, 1976). Mel-frequency cepstral coefficients (MFCCs) are a compact feature representation used in audio signal classification (Tzanetakis and Cook, 2002) and speech signal processing. The benefit of using MFCCs over cepstrum coefficients alone is that the mel scale models the non-linear human perception of pitch. The sounds generated by a flute are filtered by the player's embouchure and the airflow caused by the internal bore of the instrument. These geometries affect the envelope of the short-time power spectrum and MFCCs are able to accurately represent this envelope.

In order to calculate MFCCs a number of steps are implemented. 1) The signal is segmented into frames of 20–40ms in length, an optimal length in order to collect enough data for a detailed spectrum without there being too many changes in the signal. 2) For each frame the FFT is computed. 3) In order to align this with human hearing, the output of the FFT is passed through a number of triangular bandpass filters representative of the Mel scale, a non-linear scale that is based on human auditory perception. 4) As humans perceive loudness on a logarithmic scale, the logarithm of the signal is computed. 5) A discrete cosine transform is applied to the outputs from the last step. This transforms the frequency domain into a time-like domain known as quefrency and the outputs are known as cepstrum features (Aarabi, 2006). Audio analysis does not usually require the use of all MFCCs and it is typical to use between 4 and 20 (Lerch, 2012).

The mel scale is a perceptual scale of pitches with a reference point of 1000 mels to 100 Hz, 40dB above the listening threshold (Stevens et al., 1937). The frequency intervals are equally spaced when judged by a human listener. There are several formulae to convert from f Hz to m mels, a common example is:

$$m = 2595 \log_{10}\left(1 + \frac{f}{700}\right). \tag{4.3}$$

MFCCs are coefficients that make up an MFC and are formed by taking the DFT of the audio signal and mapping the log of the power spectrum on to a number of frequency bins on the mel scale using overlapping triangular filters. If $\widetilde{O}_k, k = 1, ..., L$ is the output at the kth filter, MFCCs are calculated using:

$$c_m = \sum_{k=1}^{L} \left(\log \widetilde{O}_k\right) cos \left[m \left(k - \frac{1}{2}\right) \frac{\pi}{L}\right], m = 1, ..., L. \tag{4.4}$$

MFCCs are the amplitudes of the spectrum computed using the DCT (Logan et al., 2000).

Mel-frequency cepstral coefficients (MFCC) features (Logan et al., 2000) have been used in automatic music genre classification by Tzanetakis and Cook (2002) who proposed a framework for the development and analysis of features for music content analysis. MFCCs were implemented due to their efficient representation of spectral data. Since then, several authors have proposed systems using MFCC features for genre and artist identification. Li and Ogihara (2004) implemented a semi-supervised learning system with timbral features such as MFCC, spectral centroid, rolloff and flux as input alongside lyrical content. Mandel and Ellis (2005) used support vector machines (SVM) to identify a single popular music performer from a group of 18 in the *uspop2002* corpus (Ellis, D. et al., 2003; Berenzweig et al., 2004). Input features were compressed into 20-band MFCCs extracted using the method described in Pachet and Aucouturier (2004). An important feature of this study was to explore and negate the album effect where songs from a single album are spectrally more similar than songs from different albums (Whitman et al., 2001; Kim et al., 2006).

4.2 Onset detection

Keegan (2010) identifies ornamentation, articulation, phrasing, and variation as important stylistic techniques for the traditional musician. To enable identification of these features through automatic signal analysis it is important to accurately establish the onset timings of new notes and other events such as ornaments and breaths.

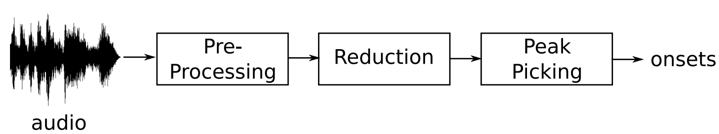


Figure 4.1: Idealised onset detection system showing preprocessing, reduction, and peak picking.

An overview of onset detection techniques is provided in the tutorial by Bello et al. (2005), describing the discrete steps of preprocessing, reduction to a detection function, and peak picking in order to define onset points (see Figure 4.1). Firstly, it is important to understand the terminologies used in describing the note signal, namely attack, transient, and onset. The attack is the time period when the amplitude of the note increases. By contrast, the transient is any part of a note where the signal is changing, often unpredictably. In flute recordings, this is the time taken for the flute to become fully energised and start to produce a stable note. In most cases, the point at which the transient commences or can be detected is the onset (see Figure 4.2) (Bello et al., 2005).

Playing a traditional flute melody creates a dynamic audio signal. In order to automatically detect a player's style in audio signals, a critical step is to accurately segment the audio into individual events. Generally, these events are found at the leading edge of the note's amplitude envelope. As ITM is typically played legato, the offset of one event is often concurrent with the onset of the next (Duggan, 2009). Events can be classified into notes, ornaments and breaths, and ornaments can be further classified into a number of individual types as discussed in Section 2.5.1.

The attack transient in traditional instruments is difficult to study because resonances are increasing in magnitude and the instrument is in a state of flux before a steady-state is achieved (Masri and Bateman, 1996). Onset detection in wind instruments is considered difficult because of the time taken for the attack phase to reach a maximum onset value. This gradual change in energy is known as a soft onset (Zhou and Reiss, 2007). In addition, notes may change in volume and the music may consist of fast arpeggios, note transitions and ornaments (Gainza et al., 2004a).

There are relatively few studies that concentrate specifically on onset detection in ITM and even fewer that use wind instruments like flute and tin whistle as subjects. A number of approaches have been attempted including signal analysis and machine learning methods. Early approaches include work by Foster et al. (1982) and Chafe et al. (1982), who developed algorithms using amplitude thresholding and pitch detection. These approaches were suitable for monophonic sources but difficulties arose in underdetection and overdetection, although Chafe and Jaffe (1986) found that existing algorithms could be combined in order to optimise detection.

4.2.1 Preprocessing

In some cases, it is necessary to prepare the signal for onset detection before reduction and peak picking. Although an optional step, preprocessing is often of central importance due to the subsequent analysis being performed. Two methods are particularly relevant and are described in the literature. The first technique involves identification of the transient section of the note and the second is sub-band decomposition, filtering the signal into a number of frequency bands (Bello et al., 2005).

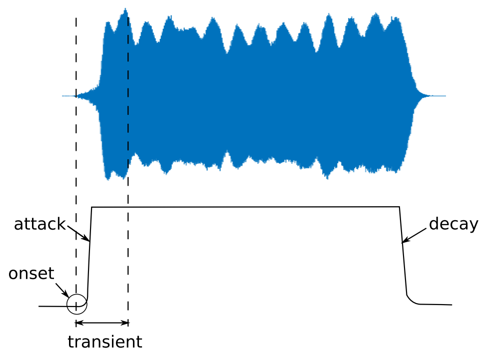


Figure 4.2: Attack, decay, and transient applied to flute note.

4.2.1.1 Transient detection

Bello et al. (2005) discuss the early section of a note with the transient commencing, in most cases, at the point of onset and ending at a point after the attack phase has completed (see Figure 4.2). As the signal is still evolving, often unpredictably, strategies have been developed to identify transients. One such strategy is the use of spectral modeling synthesis (SMS) where steady-state components are subtracted from the input signal, leaving the transient energy (McAulay and Quatieri, 1986; Serra and Smith, 1990). This technique is better suited to detection of fast, percussive onsets because slower onsets like notes from woodwind and bowed instruments can change pitch without large changes in energy. Levine (1999) separated the audio into sinusoidal, transient and noise components and was able to segment the audio into transient and non-transient regions. Duxbury et al. (2002) detected transient energy in high frequencies using an energy-based detector and coupled this with frequency-based detection in lower sub-bands to improve detection of softer onsets.

4.2.1.2 Frequency bands

Sub-band decomposition or filtering the signal into a number of spectral bands is often non-adaptive and relies on fixed parameters like frequency bands, reducing interference from instruments or sounds that occupy other parts of the spectrum (Scheirer, 1996; Klapuri et al., 2006). Bandpass filters are often designed to replicate auditory scales such as musical pitch or mel scale. These filters are often used at the preprocessing stage of an onset detection system. Bilmes (1993) developed a system using high and low pass filters, treating each separately and combining them at the end. Smith (1994) used a 32-channel logarithmically-spaced filterbank with a frequency response of 100 Hz to 10 kHz and a response based on the human cochlea model proposed in Moore and Glasberg (1983).

Scheirer (1996) built on these earlier approaches, dividing the signal into six bands spaced approximately an octave apart, the lowest having a low pass to 200 Hz and the highest band being a high pass filter at 3.2 kHz. Klapuri (1999) extended the work of Scheirer (1996) by developing a system with 21 filters from 44 Hz to 18 kHz, each aligned to one of the critical bands in the human auditory system. The three lowest bands cover an octave each and the 18 remaining are third-octave bandpass filters. Onset detection methods related to psychoacoustic loudness models perform better on non-pitched percussive sources than pitched non-percussive sources (Collins, 2005b).

Frequency bands can also be spaced to facilitate filtering of different musical notes. Chafe and Jaffe (1986) developed a system using spectral transformation based on Chafe et al. (1985) where a constant-Q filterbank is used for pre-processing. The constant-Q approach allows the frequency bin width to vary exponentially according to the frequency, thus minimising the effect of higher frequency notes being covered by multiple linear-spaced filters. As the filterbank was based around semitone steps, this also allowed the system to identify individual notes during monophonic and polyphonic passages.

Duxbury et al. (2002) noted that Masri (1996) relied on high frequency energy to detect strong transient events returning high precision in onset timing. This type of onset detection method does not work well with instruments that produce soft onsets like violin and flute, as players are able to change note without variation in high frequency energy due to the notes being excited constantly. In this case the change in lower frequency content is a more accurate note onset indicator, unlike Klapuri (1999) where the same detection function is used on each frequency band.

There has been very little research into note onset detection methods for use with instruments used in the playing of Irish traditional music. Gainza et al. (2004a) developed a method for onset detection of tin whistle signals using sub-band decomposition with 14 sub-bands centered around the individual diatonic notes of the instrument. In this system the threshold for each band was set according to acoustic theory and knowledge of the instrument, with the pressure required to sound a satisfactory note being proportional to the frequency of the note. Using these parameters, threshold levels were set automatically.

Kelleher et al. (2005) modified this system for onset detection of traditional Irish fiddle, another instrument with slow onsets widely played in the Irish tradition. In this case, the system used 29 sub-bands centered on semitones to reflect the range of the instrument as well as its chromatic nature. Using the method described in Duxbury et al. (2002), the threshold for each band was calculated by analysing the energy envelope and determining levels of probability of a transient occurring or not occurring. Using the first derivative of the signal as slope detection and the second derivative as a measure of concavity, the threshold could be set at the maximum of the second derivative. This allowed stronger and weaker onsets to be detected and an overall onset detection function will combine the outputs from all sub-bands.

A filterbank based on semitone widths was also used by Pertusa et al. (2005) who noted that there are variations in intensity and frequency of harmonics during sustain and release phases of some notes, occasionally resulting in false onsets being detected due to the spectral flux maxima being shifted to an adjoining band. The use of filter bands of one semitone in width minimised this effect as most of the spectral energy was concentrated in the centre frequencies of the bands.

The system used in Kelleher et al. (2005) was the basis for an onset detection algorithm used to detect flute signals in Köküer et al. (2014a). Using sub-band decomposition, the 14 bands were positioned one octave down from the filterbank used in Gainza et al. (2004a) as these reflected the notes of the flute.

4.2.2 Reduction

Bello et al. (2005) considers the reduction stage of an onset detection system to be the most important. A continuous feature vector detection function is calculated by downsampling the audio input using a window-based function and processing it in order to emphasise features that contribute to onset detection.

Reduction strategies are generally based on temporal or spectral signal features, or use probability models in order to provide a signal optimised for peak picking (Bello et al., 2005).

4.2.2.1 Temporal domain

Early attempts at reduction strategies worked exclusively in the time domain. The method described in Schloss (1985) was based on detection of an amplitude increase at the point of onset, meaning that percussive onsets could be detected by rectification and smoothing, or low-pass filtering the signal. Gainza et al. (2004a) developed a system to specifically detect the slow onsets associated with tin whistles. Using STFT analysis and sub-band decomposition with filters optimised for the frequencies around each separate note (see Section 4.2.1.2). This method was also used in Kelleher et al. (2005) on Irish fiddle signals, and Kelleher (2005) on Irish flute and fiddle signals. The approach was further developed in Köküer et al. (2014a) where adaptive thresholds were used, based on the time difference between peaks in the detection function.

4.2.2.2 Fundamental frequency

Several methods have also explored the use of the fundamental frequency F_0 as part of onset detection methods. Collins (2005a) developed an onset detector using the constant Q transform pitch tracker presented in Brown and Puckette (1993). The test dataset consisted of pitched non-percussive musical instruments containing notes with soft onsets. Holzapfel et al. (2010) also reported onset detection using pitch to be beneficial for soft onset detection, combining phase, magnitude and pitch to create a method of onset detection tested on Turkish folk instruments including violin.

The onset detection method presented in Köküer et al. (2014a) used pitch detection in the form of the YIN algorithm De Cheveigné and Kawahara (2002). In order to detect the F_0 a number of steps are proposed starting with the autocorrelation function (ACF) where a signal is dot multiplied with a time-shifted version of itself in order to define a series of output indicies or lags. The output response to a periodic signal will show peaks at multiple time lags representing the period and the highest non-zero-lag peak is chosen. The ACF is sensitive to changes in signal amplitude, resulting in errors where incorrect peaks are erroneously chosen. A number of error correction methods are used to minimise these effects before calculating a single threshold and frequency estimate (De Cheveigné and Kawahara, 2002). Using YIN with flute signals initially resulted in doubling errors where notes were identified as being an octave above their actual frequency. Accuracy was improved with the use of the PYIN algorithm where the single threshold is replaced with a hidden Markov model that evaluates candidate frequencies based on probability in order to minimise such errors (Mauch and Dixon, 2014).

4.2.3 Peak picking

The stage of the onset detection process after reduction is that of peak picking, where discrete time locations are automatically identified. Methods vary from defining local maxima to using adaptive thresholds or probabilistic functions. A number of algorithms are based on the first order difference function of the signal's amplitude envelope, identifying the note onset where there is a localised maximum slope or maxima above a threshold (Bilmes, 1993; Goto and Muraoka, 1995; Scheirer, 1996; Goto and Muraoka, 1996). Bello et al. (2005) defines this as $d(n) \geq \delta$ where δ is a positive constant and $d(n)$ is the nth sample of the detection function. Local maxima are often difficult to detect due to variability in size or masking due to non-musical artefacts such as noise or musical artefacts including vibrato (Bello et al., 2005). It is often impractical where low volume sounds characterised by slow onsets take some time to reach a local maxima, or where the initial rise in amplitude is not monotonal though this can be alleviated by using a range of frequency bands as part of the detection (Klapuri,

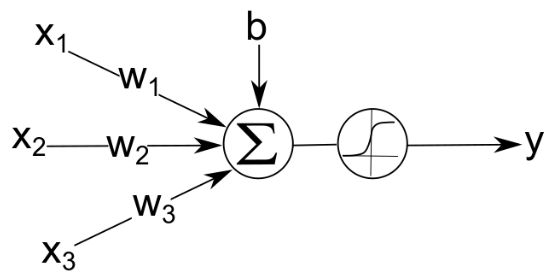


Figure 4.3: A node of a neural network with three inputs x_1, x_2, x_3, weights w_1, w_2, w_3, bias b, transfer function Σ, sigmoid activation function and output y.

1999).

Fixed thresholds can be used on sound sources with a small dynamic range but most music exhibits substantial changes in loudness over the course of the performance. Bello et al. (2005) discusses the use of adaptive thresholds $\tilde{\delta}[n]$ in order to compute a smoothed version of the detection function. Linear smoothing can be achieved by using a low-pass finite impulse response (FIR) filter.

4.2.4 Onset detection using neural networks

Machine learning is a field of computer science in which existing data is used to predict future responses. Models are trained to map inputs to correct outputs using unsupervised or supervised learning. Unsupervised learning is used to show clusters of related data where there is no right answer. In supervised learning, a model can be trained by applying labelled data, specific data that has been validated by humans to contain correct classified outputs based on inputs, also known as ground truth data. The training process involves modifying the model's internal structure in order compute expected output classes based on inputs (Paluszek and Thomas, 2016).

Neural networks are a type of supervised machine learning model consisting of nodes (see Figure 4.3) that receive a number of inputs, shown as x_1, x_2 and x_3, each multiplied by a corresponding weight, w_1, w_2 and w_3, and the three products are added together with an overall bias b to create a weighted sum. The weighted sum is entered into an activation function that determines the output y. Early neural networks consisted of a single layer of nodes between the inputs and outputs but later architectures are often more complex, containing several layers of nodes known as hidden layers. These are commonly known as deep neural networks (Kim, 2017).

MIR tasks including onset detection were undertaken using engineered features and architectures. At the time of writing, many state of the art generalised onset detection methods use probabilistic modelling techniques and deep learning architectures (Dieleman and Schrauwen, 2014). The number of onset detection methods using neural networks has substantially risen since Lacoste and Eck (2005). In this algorithm, a neural network is used between the computation of a spectrogram, a representation of the signal's spectral energy, and the use of peak picking to define note onsets. The input signal is divided into 100 ms windows and a target trace signal is created using STFT and constant Q (Brown and Puckette, 1992) transforms. The logarithm of the signal magnitude is used to aid detection of low-amplitude onsets. This information, along with a trace showing the position of musical beats, is used as an input to the trained neural network in order to create an onset trace. Based on these inputs, the network classifies 100 ms frames into one of two classes, onset or non-onset.

The network used in Lacoste and Eck (2005) is a feed-forward neural network (FNN) where signals travel only from input to output. OnsetDetector by Eyben et al. (2010) utilises bidirectional long short-term memory neural networks (BLSTM), and performs well in a range of onset detection tasks including solo wind instruments. Where a FNN classifies all input frames independently, recurrent neural networks (RNN) add backward connections. Bidirectional recurrent neural networks (BRNN) use two RNNs, one forward and one backward, thus classifying each input frame in the context of events before and after. The advantage of this type of network is that it is dynamic and the internal state of the network will change in reaction to changes in input.

The Super Flux onset detection algorithm (Böck and Widmer, 2013b) addressed the issues of false positives detected as a result of vibrato, a modulation affecting pitch that is often present in string or vocal recordings. Using the spectral flux onset detection algorithm presented in Masri (1996), a magnitude spectrogram is used as the onset detection function and is weighted based on local group delay information in order to negate picking of peaks based on the recurring pitch shifts found in vibrato. Complex Flux extended this original algorithm to include suppression of tremolo, a modulation affecting amplitude (Böck and Widmer, 2013a). Alternatively, in an approach similar to edge detection in computer vision, Schlüter and Böck (2013) implemented a CNN (CNNOnsetDetector) that was trained to detect onsets in spectrogram excerpts.

The Music Information Retrieval Evaluation eXchange (MIREX) holds an annual competition for MIR tasks including note onset detection. Onset detection algorithms are scored using F-measure, based on precision and recall (see Section 4.2.5).

A trained neural network should be capable of classifying each frame into one of two classes, *onset* or *no onset*. Eyben et al. (2010) states that picking the output node with the highest activation is ineffective and uses only output activation of the *onset* class with thresholding and peak detection. Due to the changing and dynamic nature of the music, an adaptive threshold must also be used prior to peak picking. The output activation function is not affected directly by the input amplitude as it is a representation of onset probability rather than strength. A fixed threshold δ, proportional to the median of the activation function (frames $n = 1...N$), can be used for each separate recording. This is constrained to the range from $\delta_{\min} = 0.1$ to $\delta_{\max} = 0.3$

$$\tilde{\delta} = \lambda \cdot median\ \{a_o(1), ..., a_o(N)\}\,, \tag{4.5}$$

$$\delta = min(max(0.1, \tilde{\delta}), 0.3), \tag{4.6}$$

where $a_o(n)$ is the output activation function and λ is a scaling factor used to maximise the F_1 measure on the activation set. The onset function $o_o(n)$ contains values greater than the threshold:

$$o_o(n) = \begin{cases} a_o(n)\, for\, a_o(n) > \delta, \\ 0\ otherwise. \end{cases} \tag{4.7}$$

Using a peak search to find the local maxima of the onset detection function $o_o(n)$, onsets $o(n)$ are computed by:

$$o(n) = \begin{cases} 1\, for\, o_o(n-1) \leq o_o(n) \geq o_o(n+1), \\ 0\ otherwise. \end{cases} \tag{4.8}$$

Böck et al. (2012a) found that in comparison to signal-based onset detection methods, the the onset activation functions of neural network methods have a lower noise floor and peaks at onset positions are much clearer. This allows a low threshold to be used for onset detection but in this case an offset of two frames (20 ms) can be used to prevent repeated false positive detections. Occasionally, a slow rising activation function that exceeds the threshold could result in false positives and this can be minimised by using a secondary threshold based on local maxima.

4.2.5 Evaluation of onset detection methods

The standard method of evaluating onset detection methods is to use the F-measure and this is based on two other measures, precision P and recall R. In classification tasks, data can be classes as relevant and non-relevant and correctness is defined as the ability to positively identify relevant events. In the case of the *ITM-Flute-99* dataset, relevant data is manually annotated or ground truth data. Positive identification is successful if the algorithm detects an onset within a suitable window of acceptance of the ground truth onset.

Relevant items that are correctly identified are known as *true positives* (tp), while relevant items that are not identified are *false negatives* (fn). Identified non-relevant events are known as *false positives* (fp). Precision (P) is calculated by dividing the number of *true positives* by the the overall number of found onsets (*true positives* added to *false positives*):

$$P = \frac{tp}{tp + fp}. \tag{4.9}$$

Recall (R) is calculated by dividing the number of *true positives* (tp) by the the overall number of positives (*true positives*(tp) added to *false negatives* (fn)):

$$R = \frac{tp}{tp + fn}. \tag{4.10}$$

The F-measure combines precision and recall to give a figure of merit:

$$F = \frac{2PR}{P + R} \times 100. \tag{4.11}$$

4.3 Flute-specific analysis of style

In this section, computational methods relating directly to flute analysis are discussed. Timbral and temporal attributes are important components of flute playing style and methods are considered in the context of stylistic analysis.

4.3.1 LTAS

As discussed in Section 4, the harmonics of musical notes are often less stable in their attack and decay transient sections than in the steady-state section of the note (Keeler, 1972). Figure 4.4 shows three separate LTAS of a D5 note played on a wooden flute, calculated using FFT with Hann window of n samples ($n = 2048$) with a $\frac{n}{2}$ hopsize. The note is segmented temporally into three equal lengths; the attack, central third, and release are shown as separate plots. Although the spectrum plots are similar, the attack phase has less pronounced spectral power at F_0 and F_1 while the frequencies above 5 kHz have a similar power spectrum to the central third. The lack of spectral power at lower frequencies will cause the early part of the sound to be harder. The release section contains more low frequency power and there is also less power above 5 kHz, giving a softer sound.

The LTAS has also been used to show spectral differences between individual flute players (Ali-MacLachlan et al., 2013) and is discussed in Study 1 (Section 5.1). Figure 4.5 shows the LTAS for

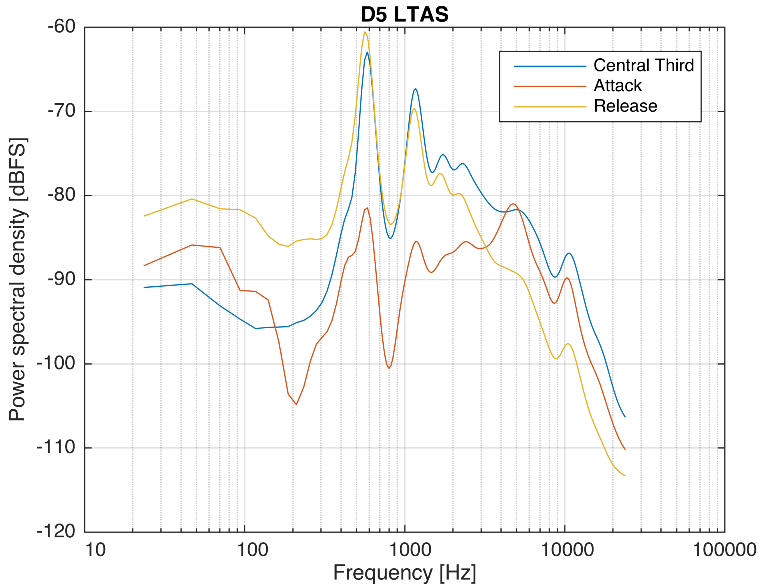


Figure 4.4: Wooden flute playing the note D5 (Attack, release and central third - F_0 = 587.33 Hz) shown as LTAS. Calculated using FFT with Hann window, length 2048 samples and 1024 sample overlap.

recordings of three players, each playing the note G4 on the same flute. Clear spectral differences can be seen between players with Player B exhibiting stronger F_1 and F_2 partials as well as greater energy levels up to 10 kHz. Player A shows weaker F_1 and F_2 partials but shows similar amounts of energy in the range 5 kHz to 10 kHz.

Figure 4.6 shows the LTAS for the same three players as in Figure 4.6 playing a G5 note. F_1 is the strongest partial and player C exhibits the strongest F_0 and F_2 partials. Player B shows greater energy levels up to 10 kHz as in Figure 4.5.

4.3.2 Short-time harmonic peak magnitudes

Although LTAS is useful for understanding the harmonic structure of a note, flute playing is susceptible to fundamental frequency changes due to shift in blowing pressure and embouchure. Short-time harmonic peak magnitudes are a compact representation of localised harmonic peaks and are useful for assessing the energy produced by different players, as shown in Figure 4.7. This shows that Player A has a consistent tone but does not have a strong 4th harmonic in comparison with players B and C. Player B and C have variable tone with player C having an overall stronger sound with more presence. This technique was used in Study 1 (Section 5.1) and Study 2 (Section 5.2) in order to compare players.

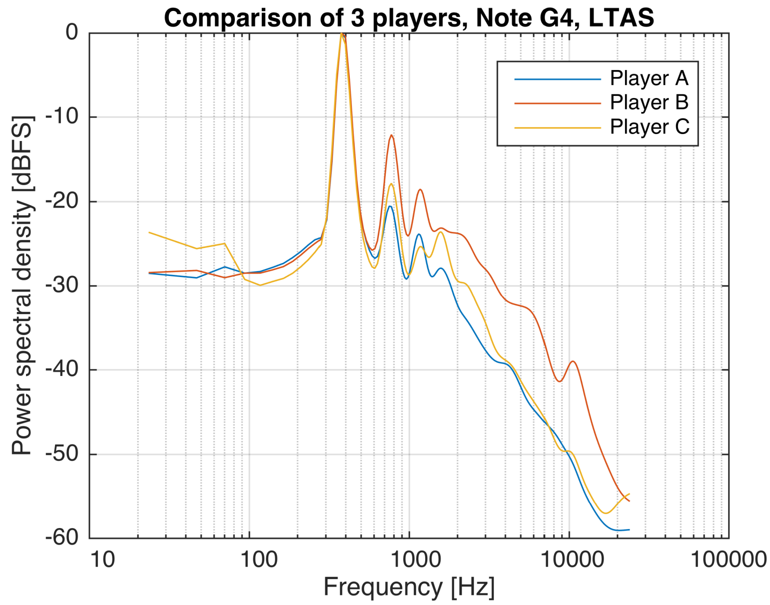


Figure 4.5: Three players with McMahon wooden flute playing the note G4 ($F_0 = 392$ Hz) (Central third of note only) shown as LTAS. Calculated using FFT with Hann window, length 2048 samples and 50% overlap, peak normalised to 0 dB.

4.3.3 MFCCs

MFCCs are a compact representation of a sound's power spectrum that reflects the non-linear nature of human hearing by using the Mel scale. A 13 coefficient MFCC is used alongside note length and chroma features as part of the training data set in Study 3 (Section 5.3) and a 40 coefficient MFCC is used in Study 5 (Section 5.5)

Figure 4.8 shows G4 notes played by three different players showing differences in MFCC magnitudes based on a filter with 13 bands. The lowest coefficient is omitted as it includes the DC offset.

4.3.4 Onset detection

There are relatively few studies in the literature that deal specifically with onset detection within ITM, particularly with reference to the flute. Onsets were found by Gainza et al. (2004b) by using band-specific thresholds in a technique similar to Scheirer, 1996 and Klapuri, 1999. A decision tree was used to determine note, cut or strike based on duration and pitch. Kelleher et al. (2005) used a similar system to analyse ornaments on the fiddle within Irish music, as bowed instruments also produce slow onsets. Kelleher (2005) employed this method to detect ornaments in a set of ten flute

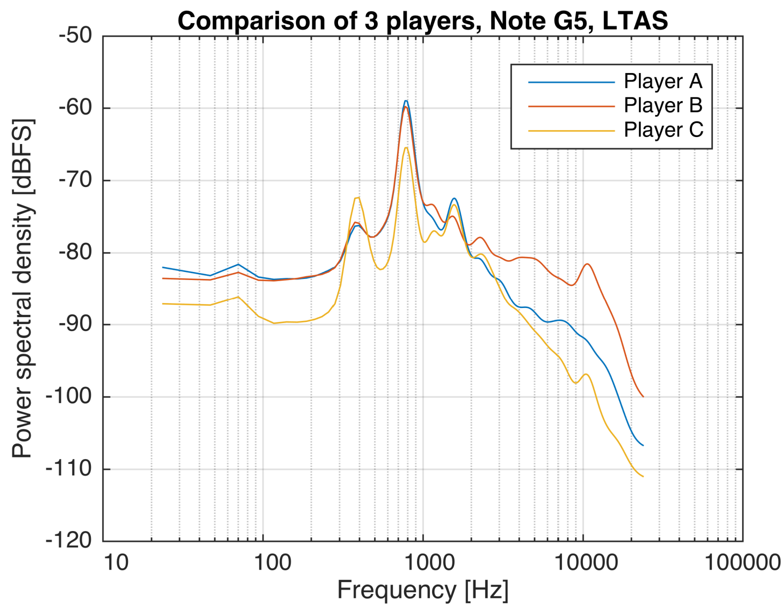


Figure 4.6: Three players with McMahon wooden flute playing note G5 F_0 = 783.99 Hz) (Central third of note only) shown as LTAS. Calculated using FFT with Hann window, length 2048 samples and 50% overlap.

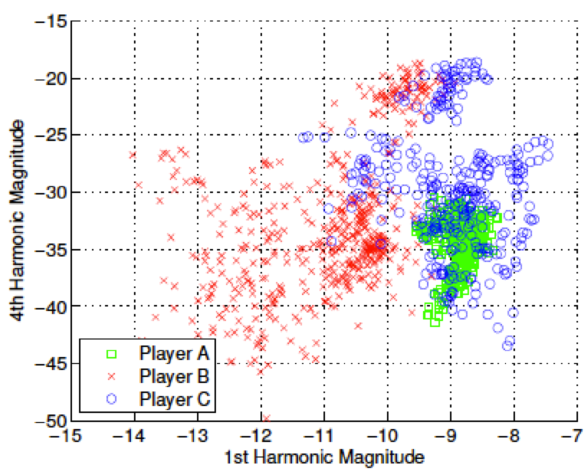


Figure 4.7: Scatter plot of short-time magnitude values (in dB) at the harmonic peaks, indicated for individual players.

recordings from Larsen (2003) achieving high average onset and pitch accuracies.

Köküer et al. (2014a) also analysed flute recordings through the incorporation of three kinds of information and a fundamental frequency estimation method using the YIN algorithm by De Cheveigné and Kawahara (2002). As in Gainza et al. (2004b) a filterbank with fourteen bands was used and these

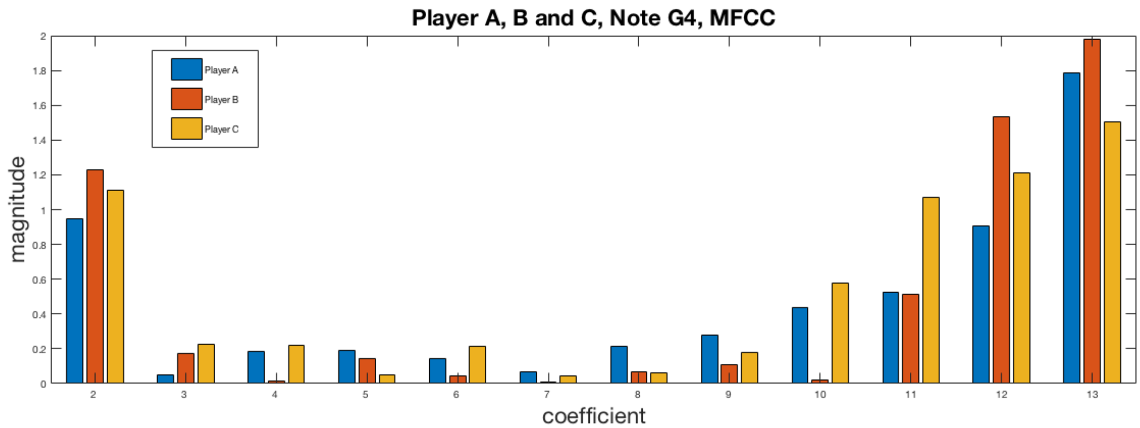


Figure 4.8: Three players with McMahon wooden flute playing the note G4 shown as MFCC with 13 band filter. Methodology for data collection is presented in Ali-MacLachlan et al. (2013).

were optimised for the notes on an unkeyed flute. More recently, Jancovic et al. (2015) presented a method for transcription of ITM flute recordings with ornamentation using hidden Markov models and Beauguitte et al. (2016) evaluated note tracking using a range of methods on a corpus of 30 tune recordings.

Kelleher et al. (2005), Köküer et al. (2014a) and Jancovic et al. (2015) use a corpus of flute recordings accompanying Larsen (2003) that includes tutorial recordings not representative of typical playing. This is indicated in Table 3.3 in the columns marked Kelleher, FMA14 and ISMIR14.

In MIREX 2015, the highest F-measures returned in the Solo_Winds class were ComplexFlux.2015 (74.6%) and OnsetDetector.2015 (74%), both by Böck. The F-measures for the highest performing onset detection methods in the Solo_Winds class in 2016 were CNNOnsetDetector by Schlüter and Böck (77.9%), LR1.2016 by Liang, Su and Yang (73.8%), and ComplexFlux.2016 by Böck (72.5%). Böck's work is available as part of the Madmom signal processing library (Böck, 2017).

In Study 3 (Section 5.2) the performance of 11 note onset detectors was measured and in Study 4 (Section 5.4) an onset detection method using a Convolutional Neural Network trained on flute recordings was implemented.

4.4 Chapter summary

This chapter provides a summary of the computational techniques required to analyse stylistic differences between traditional flute players. The ability to accurately compute note onsets and timbral content are of particular importance when defining differences between players in this field. The flute produces soft onsets making the task more difficult than for instruments producing a defined percussive note onset and this requires particular attention in order to preserve the accurate timings necessary for successful note segmentation.

Chapter 5

Computational analysis of style in ITM flute playing

This chapter presents methods for the automatic identification of stylistic features within Irish traditional flute playing. This includes methods for automatic event detection and their use in the analysis of the stylistic features discussed in Section 2.5.

In the tradition of ITM, players from different backgrounds are individuated based on their use of techniques such as ornamentation, a key factor alongside melodic and rhythmic variation, phrasing and articulation in determining individual player style (McCullough, 1977; Hast and Scott, 2004). To automatically detect a player's style in audio signals, it is important to be able to reliably detect timbral features as well as notes and ornamentation types. This analysis will aid understanding of the relationship between musicians, their instruments and the music they produce along with their connection to wider traditional music.

Historically, players would be influenced by leading local musicians and this in turn led to localised or regional playing styles. In a more modern context, communications technologies and mobility have resulted in flute players who are influenced by recordings and concerts featuring leading players. This is coupled with a strong desire to play local sessions, informal meetings of fellow ITM players. A precursor of developing one's own musical playing style is the emulation of well-known or favourite players, either tonally or by using the same type of ornamentation. As an oral tradition, the act of sharing and teaching traditional melodies inevitably involves the passing on of stylistic influence. Since the availability of ITM on 78 r.p.m. records in the early 1900s, traditional musicians have used recordings as a way to learn repertoire and this led to the emergence of a standardised style and the demise of strong regional styles (Edmondson, 2013).

Timbre is an important contribution to an overall playing style. The flute's sound is an integral stylistic component that can be varied from soft and airy to hard-edged and piercing. When describing another musician's style, flute players will often define tonal qualities and use of ornaments as if they are two elements of a compound, individual but bound together. McCaskill and Gilliam (2004) note that in order to rise above the sound of other players or dancers, the Irish flute player must "achieve a biting, crisp and piercing sound". Classical players achieve changes in tonal colour through manipulation of embouchure and mouth cavity but these variances are not important in ITM. Instead the focused sound is achieved by rotating the head joint towards the player, thus directing more air into the body of the flute. The sound is also made possible by a powerful stream of air requiring the use of the diaphragm as well as lungs (McCaskill and Gilliam, 2004). According to Larsen (2003) a flute player will inhale up to eight pints of air in under half a second and develop an embouchure that allows for its slow release while producing a consistent tone.

5.1 Study 1: Quantifying timbral variations

An exploratory study aimed to evaluate whether material has an effect on flute timbre. In comparison to Widholm et al. (2001) where all flutes were of the same design but different materials, this study reflected the different materials and concert flute designs available to a typical ITM player. Recordings were made of a range of individual notes played by three representative players: beginner, intermediate and expert, on each of six different flute models. The analysis was then performed using recordings of the sustained part of G_4 notes. This allowed the player's timbre to be measured on a note that is easy to play due to being in the lower octave, and analysis excluded the unstable attack and decay sections in favour of the central portion of the note. The timbre is determined by the spectral harmonic content and analysis was performed by employing the LTAS (see Section 4.1.2) and the short-time magnitude values at harmonic peaks (see Section 4.1.1). The findings of this study were published in Ali-MacLachlan et al. (2013).

5.1.1 Method

For this analysis a set of flutes were selected to reflect the varying properties possible in wooden concert flutes. This was aimed at being reflective of the full representation of concert flutes available and cover several alternatives in manufacturing material and style. The flutes used, with their specifications, are presented in Table 5.1.

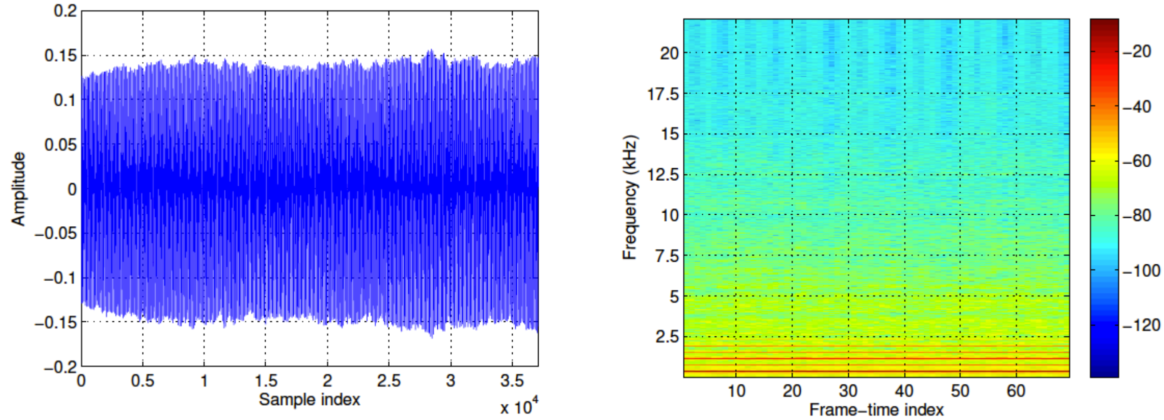
ID	Manufacturer	Keys	Material	Foot	Design
1	deKeyser	0	African Blackwood	C	Pratten
2	Dixon	0	Polymer	D	Rudall & Rose
3	McMahon	0	African Blackwood	C	Rudall & Rose
4	Sweetheart	0	Maple	D	Sweetheart
5	Vignoles	0	African Blackwood Polymer Head	C	Pratten
6	Wallis	8	African Blackwood	C	Wallis

Table 5.1: Flutes used in study.

Each of the flutes used in this study is manufactured by a respected flutemaker that specialises in the manufacture of wooden concert flutes. Arie deKeyser is a Belgian national resident in Swords, Co.Dublin and has manufactured flutes as well as uilleann and Flemish bagpipes since the 1980s (deKeyser, 2017). Tony Dixon is a Devon-based manufacturer of predominantly polymer-based flutes and tin whistles who started manufacture in 1997 (Dixon, 2017). Brendan McMahon was a flute maker and player from County Clare, Ireland. Sweetheart flutes were built in Enfield, Connecticut, U.S. by Ralph Sweet (Sweet, 2017). Michael Vignoles is a maker of flutes, bodhrans and uilleann pipes in Galway, Ireland (Vignoles, 2017) and Joseph Wallis was a London-based instrument maker from 1848–1928.

Recording controls were maintained throughout the experimentation. These included the use of a semi-anechoic chamber and a controlled microphone position 20 cm away from and approximately one third of the distance between the head and the foot. The position was chosen to maintain tonal balance and minimise direct wind noise from the embouchure hole. Recordings were collected using a DPA 4090 microphone with a flat frequency response between 20 Hz and 20 kHz (+/-2 dB) (Robjohns, 2006) and is therefore suitable for measurement recordings of this type. The audio signal was sampled at 44.1 kHz.

Three players were selected for the experiment, with considerable variance in playing experience. Player A has approximately 10 years of experience playing in bands and at sessions, player B has approximately 25 years playing in bands and at sessions but additionally learned flute and whistle at a young age, competing and winning in the junior section of the All-Ireland Fleadh. Player C is an experienced woodwind player and repairer who normally plays clarinet but has less than a year's experience playing flute.



(a) **(b)**

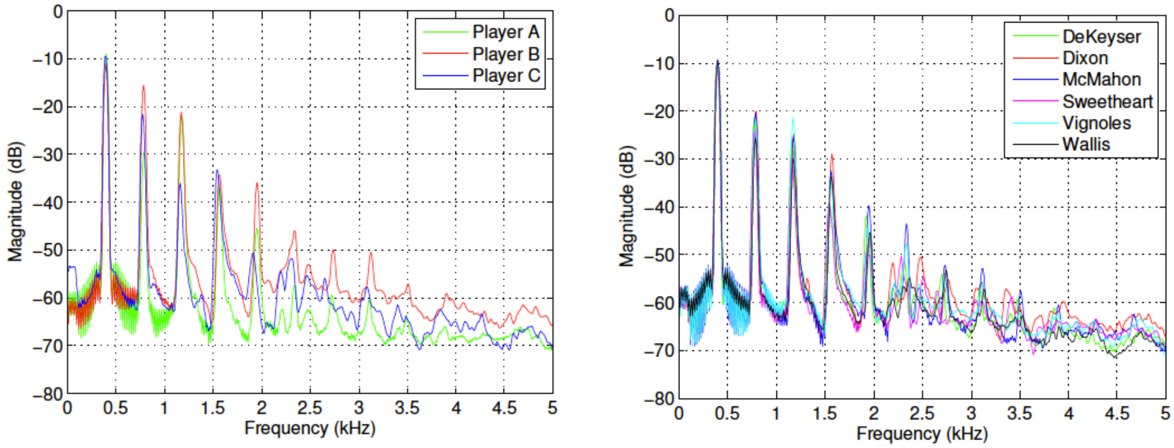
Figure 5.1: Wallis flute playing note G_4: Waveform (a) and corresponding spectrogram (b).

The note G_4 was selected for analysis in this study. It is one of the easier notes to play as it is not overblown and requires only three toneholes to be covered. Playing the lower notes on the flute requires attention to the pressure as well as the size of the lip opening (Bamberger, 2004), and playing an unfamiliar flute also adds to this difficulty. In order to gain consistency, each player spent time acclimatising to each flute and then played a scale of D starting with D_4 to ensure that the G_4 was played naturally.

5.1.2 Analysis

Volume differences between the recordings are normalised to ensure that each recording has the same average energy. The sampled audio signal of each recording is then processed using short-time Fourier analysis. The signal $x(n)$ is segmented into short overlapping analysis signal frames, with the length of the frame N set to 2048 samples (corresponding to approx. 46 ms) and the shift between adjacent frames L set to 512 samples. Each signal frame is multiplied by the Hamming window function. The windowed frames are then zero padded up to 4096 samples, and the Fourier transform is applied to provide the short-time Fourier spectrum $X(m, k)$. The collection of the short-time magnitude spectrum over time is also referred to as spectrogram.

An example of the time domain signal (with the attack and decay sections removed) and its corresponding spectrogram is depicted in Figure 5.1 for player A playing a G_4 note on the Wallis flute. It can be seen that the magnitude values at frequencies above approximately 5 kHz are small. Since similar trend was also observed for all other recordings, only the frequencies up to 5 kHz were used in



(a) Average over six flutes

(b) Average over three players

Figure 5.2: LTAS of each player averaged over six flutes (a) and of each flute averaged over three players (b).

the analysis.

In order to obtain information about average spectral properties of the instruments and players, each recording was subjected to a long-term average spectrum (LTAS) analysis. LTAS analysis can provide information on sound timbre and is particularly useful when persistent spectral features are under investigation (White, 2001) and is computed by averaging the short-time Fourier magnitude spectra over time, resulting in a single feature vector representing each of the recordings.

In addition to using the LTAS, analysis was also conducted using only the information on the short-time magnitudes of the first few harmonics. In this study, the harmonics were identified semi-automatically based on the knowledge of the note played, i.e., the harmonics were located by finding peaks around the multiples of the note frequency.

5.1.2.1 Results of analysis employing LTAS

The LTAS is used to analyse the inter-flute and inter-player timbral differences. This is performed by calculating the mean LTAS of each player, obtained by averaging over the flutes, and of each flute, obtained by averaging over the players. The resulting mean LTAS are shown for each player in Figure 5.2(a) and for each flute in Figure 5.2(b). It can be seen that the mean LTAS of individual players vary mostly in the F_1, F_2 and F_4 harmonics, while the mean LTAS of individual flutes vary mostly in the F_2, F_3 and F_4 harmonic. Overall, the mean LTAS of individual players differ more than those of individual flutes. Figure 5.2(a) shows that player A is weaker on the F_1 harmonic, while player B has a strong F_1 and F_4 harmonic and player C is weaker on the F_2 and F_4 harmonic.

Figure 5.3 shows the LTAS of all the six flutes for each player A, B and C. It can be seen that there are common traits in the timbre of each player across all of their recordings with different flutes, for instance, player B has strong the F_1 harmonic consistently over all the flutes.

5.1.2.2 Results of analysis employing short-time harmonic peak magnitudes

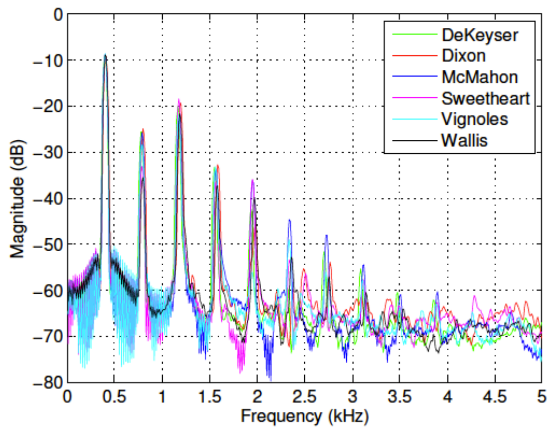
While the conventional LTAS as used above can provide useful information, it is susceptible to variations in the fundamental frequency. Small fluctuations in the fundamental frequency of the played note, caused by variance in blowing pressure or embouchure shift, result in the harmonics of each short-time spectrum becoming misaligned. This effect of misalignment of the harmonics could be avoided by using a pitch-corrected LTAS (Boersma and Kovacic, 2006), or by localising the harmonic peaks in the short-time spectrum and using only these magnitudes. Analysis in this section is performed using magnitudes of the harmonic peaks.

Standard deviation	Harmonic				
across flutes for:	F_0	F_1	F_2	F_3	F_4
Player A	0.2	4.4	1.7	1.9	7.0
Player B	0.9	1.6	5.7	6.4	7.4
Player C	0.2	1.8	5.4	5.1	5.5
Average	**0.4**	**2.6**	**4.3**	**4.5**	**6.6**

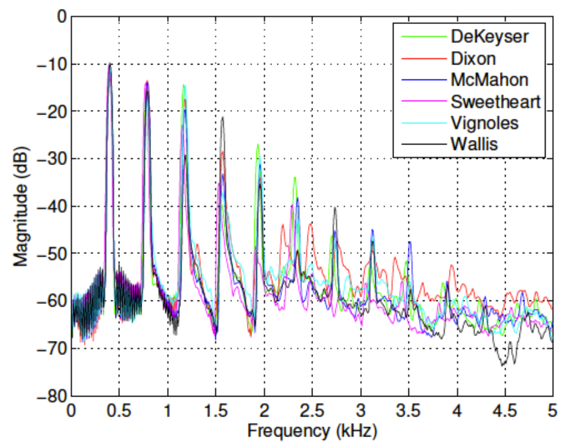
Table 5.2: Standard deviations (dB) across flutes for the first five harmonics.

First, the timbral variances between the players and flutes are quantified. For each recording, the mean magnitude value of each localised harmonic peak over all the signal frames is calculated. The standard deviation of these mean magnitudes of harmonics is then calculated for each player across the flutes, presented in Table 5.2, and for each flute across the players, presented in Table 3. It can be seen that in most cases there are smaller variations across the flutes than across players. Figure 5.4 shows the average standard deviations for each player and each flute, in both cases averaged over the first five harmonics. The overall average standard deviation across the flutes is 3.7 dB while across the players is 6.1 dB.

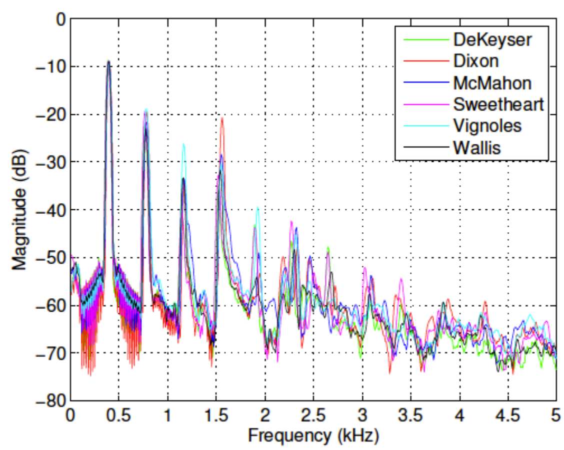
Evaluations are then performed using the short-time harmonic magnitudes of all the signal frames. In addition to the effect of players and instruments, this also shows the effect of frame-to-frame variations. Figure 5.5 depicts 2-dimensional scatter plots of the magnitudes of one harmonic peak



(a) Player A



(b) Player B



(c) Player C

Figure 5.3: LTAS of six flutes, players A, B and C.

Standard deviation across players for flute:	Harmonic				
	F_0	F_1	F_2	F_3	F_4
deKeyser (1)	2.0	5.5	14.0	2.7	9.4
Dixon (2)	1.5	5.7	9.4	6.0	9.3
McMahon (3)	1.1	6.1	7.2	3.1	9.0
Sweetheart (4)	0.8	9.8	11.3	2.0	5.9
Vignoles (5)	1.2	6.0	5.9	3.2	12.7
Wallis (6)	0.6	10.0	5.7	8.2	8.7
Average	**1.2**	**7.2**	**8.9**	**4.2**	**9.2**

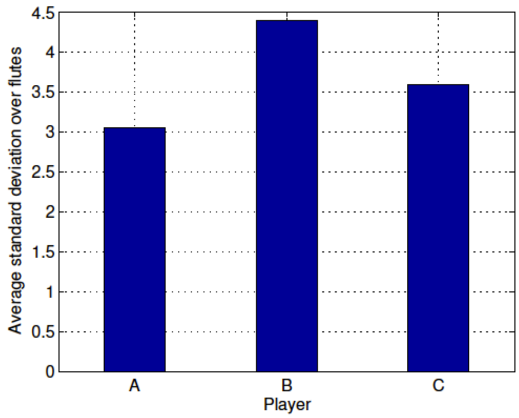
Table 5.3: Standard deviations (dB) across players for the first five harmonics.

against other harmonic peak for all signal frames of all recordings. The individual players are indicated by different shape and colour markers. It can be seen that the individual players can be well separated using a combination of the first five harmonic magnitudes. The figures show that the Player A, denoted by green square mark in Figure 5.5, is contained in few sub-clusters, corresponding to different flutes. This can be observed in Figure 5.6 depicting the same scatter plots of the 2nd (F_1) against the 3rd (F_2) and the 2nd (F_1) against the 4th (F_3) harmonics with different markers indicating individual flutes.

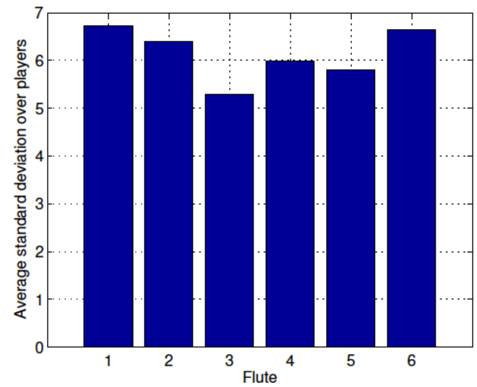
The variations for Player A within each flute are the smallest across the players, which indicates that the Player A plays each given instrument in the most consistent way, i.e., most stable timbre. This is in contrast to Player C, who shows large variations for most of the flutes, especially, Sweetheart and deKeyser. Player B shows consistently high levels of F_1 and F_2 harmonics indicating a powerful, cutting tone. Figure 5.6 also shows that the inter-player differences are larger than the inter-flute differences, confirming the results of variance analysis presented earlier.

5.1.3 Discussion

This study presented an analysis of the timbral variations in traditional Irish flute playing. The analysis were performed using isolated recordings of note G_4, played by three different players with six different flutes. After empirical analysis attack, sustain and release sections of notes are considered independently. The attack and release portions of the recordings were not used in the analysis due to being harmonically less stable. The analysis was performed by employing the LTAS due to the signal being steady-state, and also employed the short-time magnitudes of the harmonic peaks. The latter



(a) Player



(b) Flute

Figure 5.4: Standard deviations (dB) of harmonic peak magnitudes for each player (a) and flute (b), averaged over the first five harmonic peaks.

avoids the effect of any fluctuations in the fundamental frequency of the played notes. Experimental results demonstrated that the LTAS of individual players differ more than those of individual flutes. The analysis of variations of the harmonic magnitudes showed that in most cases there are smaller variations across the flutes than across the players, with the overall average standard deviation being 3.7 dB across the flutes and 6.1 dB across the players. The short-time analysis of harmonic magnitudes of all signal frames showed how consistent the timbral profile of each player was when using a particular flute.

5.1.4 Conclusions

This study aimed to evaluate whether the instrument or the player had more effect on note timbre. Although this type of study had previously been performed using metal flutes of the same design manufactured from different materials, the range of wooden flutes indicative of those used in Irish traditional music had not been explored. Using recordings of three players with different levels of experience in traditional flute playing, the study concentrated on G_4 notes.

The use of long-term average spectrum allowed a comparison between localised harmonic peaks for individual players and individual flutes. The use of harmonic peaks combined with short-time frequency magnitudes allowed the consistency of a player's timbre to be evaluated across a range of flutes.

The study showed that players are often consistent in their production of tone, and that one player

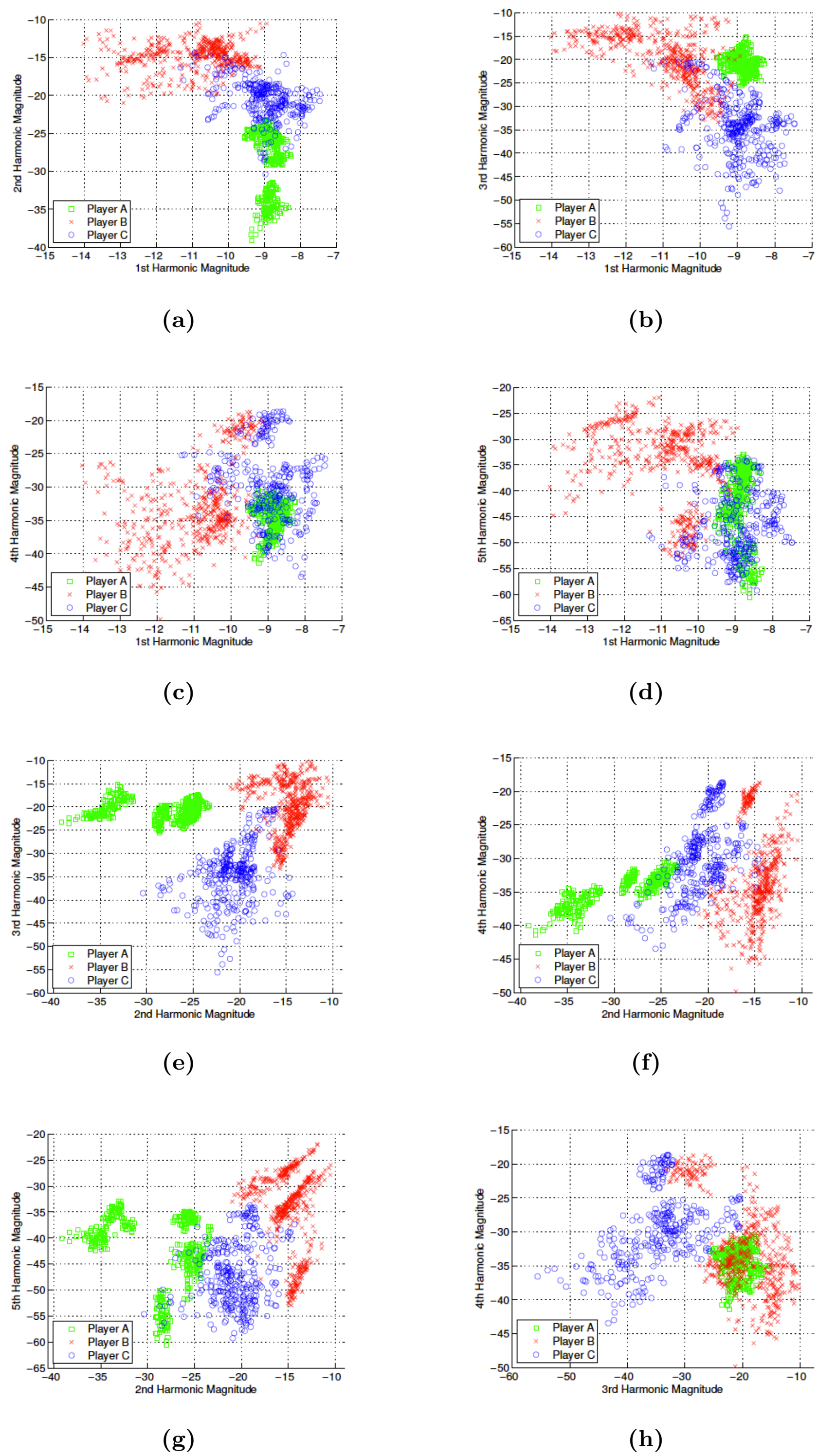
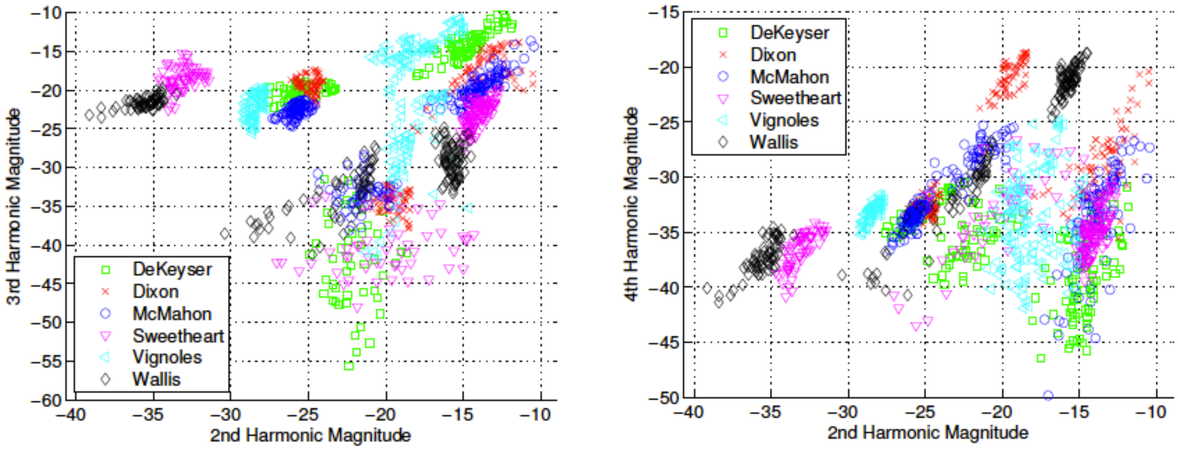


Figure 5.5: Scatter plots of short-time magnitude values (dB) at harmonic peaks, indicated for individual players.



(a) **(b)**

Figure 5.6: Scatter plots of short-time magnitude values (dB) at harmonic peaks, indicated for individual flutes.

exhibits less tonal variation over a number of flutes in comparison with one flute being played by a number of players. In order to extend this work, a larger dataset is required allowing a study using more players, a greater variety of notes and a longer duration of recordings.

5.2 Study 2: Player identification using short-time harmonic magnitudes

In order to extend the experimentation based on the findings of the study detailed in Section 5.1, a study was undertaken to attempt to identify players from notes sounded during the playing of traditional tunes. The results of the earlier study concluded that individual players produce more variation in harmonic magnitudes when compared to the difference between flutes. As the earlier study used recordings of musicians playing scales and concentrated on a single note (G_4), a corpus of solo flute recordings was collected in order to study a wider range of notes played as part of traditional tunes. The findings of this study were published in Ali-MacLachlan et al. (2015).

5.2.1 Introduction

Playing a flute requires control over breath pressure, lip position and lip aperture (Coltman, 1968b). Changes in these parameters will result in timbral differences, a contributing factor to tonal differences between players. Timbre is the quality of a musical note that distinguishes it from other notes of the same pitch and loudness. Schouten (1968) proposed five acoustic parameters to describe timbre: Range between tonal and noiselike character, spectral envelope, changes in spectral envelope and fundamental frequency over time, sound onset and time envelope.

Erickson (1975) agrees that these dimensions are excellent for perceptual analysis of music. Handel (1995) argues that there are many stable and time-varying acoustic properties but no single property fully defines timbre. Burred et al. (2010) found that temporal envelope is more valuable when distinguishing between sustained and decaying instruments. This study did not analyse notes based on temporal attributes.

Research by Santos et al. (2014) found that flute players are able to modify their timbre. Differences were found in the mean of the spectral centroid during pieces played as a duo with bassoon or clarinet. According to Halmrast et al. (2010) and Darke (2005), widespread use of metaphors to describe timbres, like “smooth," “dark," and “brilliant" show that listeners have distinct concepts of different timbres and even within single instruments like piano, specific timbral descriptors are recognised (Bernays and Traube, 2011). Keegan (1997) explains that within Irish traditional music, descriptive language is often unclear.

According to Jensen (1999) spectral envelope is often enough to identify a sound. Timoney et al. (2004) found that in spectral magnitude plots of tin whistles, a closely related instrument to the flute, there are only a small number of harmonics compared to other instruments. Chudy and Dixon (2010) presented a cello player recognition system employing timbre features, using controlled studio recordings of 6 cellists playing the same excerpt on two different cello instruments.

Utilising spectral analysis, the study described in Section 5.1 showed clear timbral differences between players with varying levels of experience, each playing single G_4 notes as part of a scale with different models of wooden flute (Ali-MacLachlan et al., 2013).

To build on this earlier study, an exploration was made into whether distinct spectral differences exist between professional players and between their playing of different notes. Furthermore, this study aimed to ascertain whether professional players could be identified based on their spectral differences in commercial recordings. The playing of five players, all at a professional level, was analysed. Musicians played reels, jigs, hornpipes and polkas, some of the most common forms of Irish traditional dance tunes.

Short-time magnitudes of the first few harmonics were used as timbre descriptors. Timbre-identity of players across the notes that have the highest usage in the corpus were investigated: D_4, E_4, $F\#_4$, G_4, A_4, B_4, D_5, E_5 and $F\#_5$. The levels of harmonics in the sustained sections of notes are used to build a model of each player. Identification results are presented as a confusion matrix with four-fold cross-validation.

5.2.2 Dataset

The recordings chosen for analysis are part of *ITM-Flute-99*. They feature the solo flute playing of Harry Bradley, Matt Molloy, Conal O'Grada, Séamus Tansey and Michael Tubridy who are prominent musicians in Irish traditional music. From the available solo unaccompanied recordings, four traditional tunes were chosen for each of the five players (note that the tunes are not the same across the players). The 20 tunes vary in length, from 17 to 41 seconds, and each tune contains between 147 and 311 events, including notes, ornaments and breaths. The tunes are identified in Section 3.3 in the column entitled FMA15.

5.2.3 Analysis

The volume differences between the recordings are normalised to ensure that each recording has the same average energy. The signal is then segmented into short overlapping signal frames. Each signal frame is multiplied by the Hamming window function. The windowed frames are then zero padded, the Fourier transform is applied, and the absolute value taken to provide short-time magnitude spectrum. The magnitude values are compressed by applying logarithm.

The recordings are accompanied by a set of label files containing note onset and offset times along with note frequencies. Short-time magnitudes of the first four harmonics are used as timbre descriptors. Harmonics were identified semi-automatically based on the annotation, i.e., the harmonics were located by finding peaks around the multiples of the note frequency provided by the label file. In this study, variations in timbre between players are explored at note level. Individual notes are extracted from entire recordings and the analysis is performed for each type of note (e.g. D_4, E_4) separately. Notes corresponding to ornaments are discarded due to their very short duration. As shown by Keeler (1972) through his work with organ pipes, attack and decay sections of notes are harmonically less stable. Thus, in order to analyse only the stable part of the notes, the sustained middle third of each note instance is used.

5.2.3.1 Visual identification using short-time harmonic magnitudes

Initially, a visual assessment of the relationship between magnitudes of harmonics was presented. For each instance of a note in each recording, the mean magnitude value of each of the four harmonics

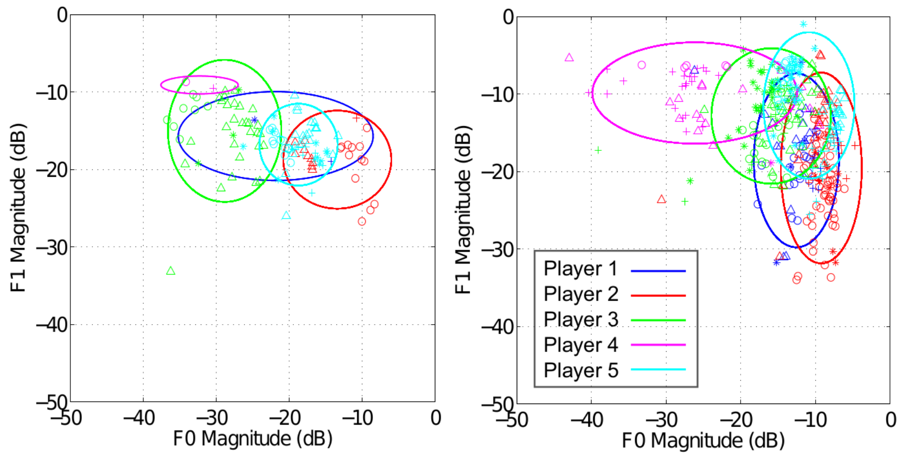


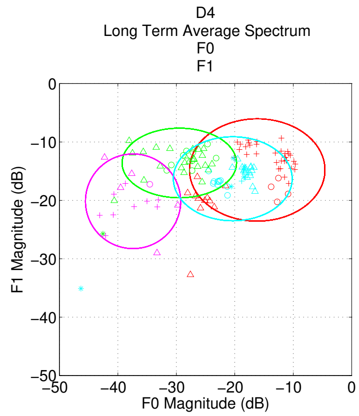
Figure 5.7: Scatter plots of short-time magnitude values (dB) at harmonic peaks F_0 and F_1 for note E_4 (left) and A_4 (right). Individual players are indicated by different colour and tunes by different shape markers. Clusters belonging to each of five players are marked by a two standard deviation ellipse for visual reference.

over the sustained middle third of signal frames, as described in Section 5.2.3, is calculated. Figure 5.7 depicts two dimensional scatter plots of the mean magnitudes of one harmonic component (F_0) against another harmonic component (F_1) for all instances of note E_4 and A_4 from all recordings. In the figure, individual players are indicated by different colour markers and four tunes belonging to each player are indicated by different shape markers. For visual reference, clusters belonging to each five players are marked by an ellipse showing two standard deviations with corresponding colour code and individual tune markers as detailed in Appendix A.1.

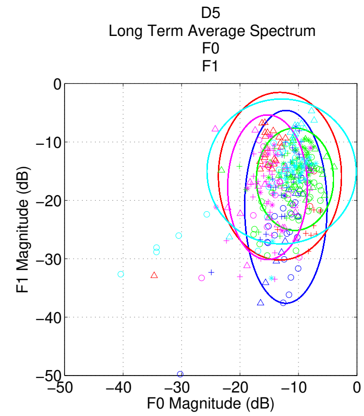
The clusters depicted in Figure 5.7 indicate that Player 3 (cyan) often exhibits equal levels at F_0 and F_1, whereas player 2 (red) has a consistent F_0 with a variance in F_1. Player 4 (magenta) often exhibits F_1 magnitudes that are higher than F_0. These trends are evident across notes in the first octave (D_4 to B_4). In the second octave these trends are much less obvious with the exception of $F\#_5$ and these differences are illustrated in Figure 5.8, comparing notes D, E and F# against their upper octave equivalents. Further examples of scatter plots showing F_0 against F_1, F_2 and F_3 are contained in Appendix A.

5.2.3.2 Gaussian mixture model classification

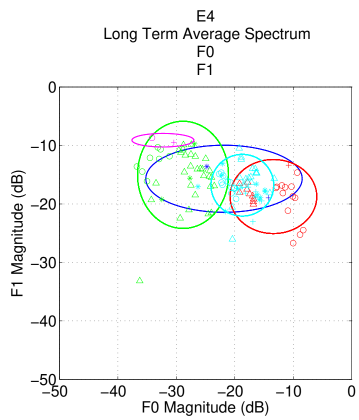
Visual representations of the data showed that there was considerable overlap of clusters, and many are not circular in shape (see Figure 5.8). This suggests that it is preferable to use a clustering algorithm



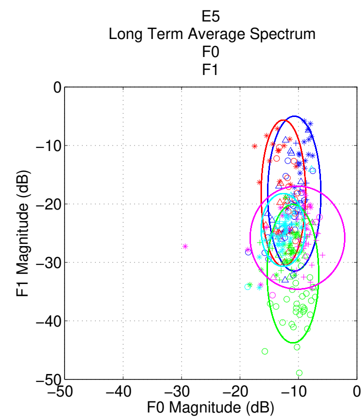
(a)



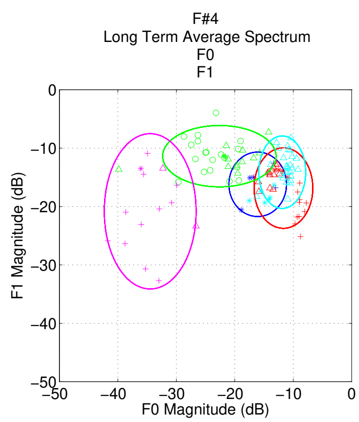
(b)



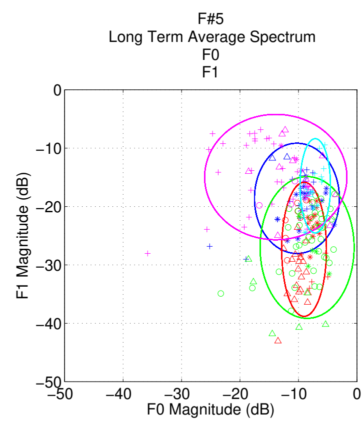
(c)



(d)



(e)



(f)

Figure 5.8: Scatter plots of short-time magnitude values (dB) at harmonic peaks F_0 and F_1 for notes D_4, E_4 and F$\#_4$ (left) and D_5, E_5 and F$\#_5$ (right). Individual players are indicated by different colour and tunes by different shape markers. Clusters belonging to each of five players are marked by a two standard deviation ellipse for visual reference.

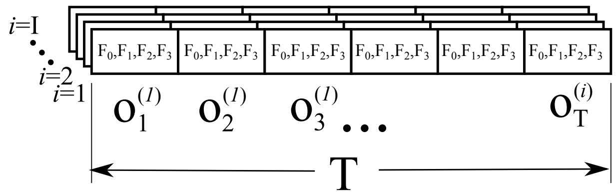


Figure 5.9: Note instances with number of frames represented by T_i, showing a sequence of feature vectors $O^{(i)}$, each containing harmonic magnitudes F_0, F_1, F_2 and F_3.

that produces soft clusters, where data can be associated with more than one cluster. In this case the Gaussian mixture model is preferable to the more popular K-means clustering algorithm (Marsico et al., 2019).

An acoustic model is created for each player k and each note n, denoted as $\lambda(k, n)$. The modelling is performed using a single multidimensional Gaussian distribution with full covariance matrix. The parameters, mean and covariance matrix of each model are estimated using the training data.

Identification of players is considered from a finite set of players based on a given piece of recording from the test data, containing one or more instances of a given note. The feature extraction step, as described in Section 5.2.3, provides a sequence of feature vectors. Considering that a given piece consists of R instances of a note, a set of feature vectors is $O=\{O^{(i)}\}_{i=1}^{R}$. Each note instance is represented by a sequence of feature vectors $O^{(i)}=(\mathbf{o}_1^{(i)}, \ldots, \mathbf{o}_{T_i}^{(i)})$, where T_i is the number of frames in the instance i and $\mathbf{o}_t^{(i)}$ is an N dimensional feature vector for frame t. $\mathbf{o}_T^{(i)}$ contains the harmonic magnitudes for F_0, F_1, F_2 and F_3, as shown in Figure 5.9. The overall likelihood of the feature set O is calculated on model of each player k for the corresponding note n as:

$$p(O|\lambda_{k,n}) = \prod_{i=1}^{R} p(O^{(i)}|\lambda_{k,n}) = \prod_{i=1}^{R} \prod_{t=1}^{T_i} p(\mathbf{o}_t^{(i)}|\lambda_{k,n}). \tag{5.1}$$

The recognised player k^* is found as $k^*=\arg\max_k p(O|\lambda_{k,n})$.

5.2.4 Experiment

The audio signal was analysed using frames of 1024 samples with 256 samples shift between adjacent frames. The windowed frames were zero padded to 2048.

4-fold cross-validation was employed to obtain more statistically reliable assessment of the performance. For each fold, three recordings from each player were combined to estimate the model for each player and note. The remaining one recording from each player was used for testing. This training and testing was repeated four times, taking a different subset as the test set each time. Overall test

E4 All Folds		Predicted Player				
		1	2	3	4	5
Actual Player	1	0	1	0	0	2
	2	0	4	0	0	19
	3	0	0	26	0	14
	4	0	0	2	0	0
	5	0	12	1	0	38

A4 All Folds		Predicted Player				
		1	2	3	4	5
Actual Player	1	29	13	7	0	0
	2	29	43	2	0	26
	3	9	3	61	10	12
	4	0	1	6	34	3
	5	0	33	30	0	23

Figure 5.10: Confusion matrices for identification of players, using single note instance in Fold 1,2,3 and 4. Totals for all folds are shown for the notes E_4 and A_4. Rows refer to the actual player and the columns to the predicted player.

performance is aggregated over the four folds.

5.2.5 Results

This section presents the results of player identification. These results are provided in the form of a confusion matrix where each row refers to the actual player and each column to the predicted player. Figure 5.10 shows examples of confusion matrices obtained when using notes E_4 and A_4 and adding total notes across all 4 folds. Table 5.4 shows the overall player identification accuracy when using individual notes. Results were obtained based on single, two and three note instances. This was computed as the percentage of correctly identified instances out of the total number of instances over five players and over four folds. It can be seen that the highest accuracy is achieved for note E_4 which is 57%, 63% and 68% respectively for single, two and three note instances. Accuracy for A_4 is 51%, 54% and 55%. Note $F\#_4$ achieved the lowest accuracy, 19%, 22% and 26% which is only little above random guess.

Table 5.5 shows identification accuracy across the 5 players. The analysis shows that players 1,3 and 4 are substantially easier to recognise than players 2 and 5.

The current performance seems relatively low and several factors may have affected the performance. The use of a single Gaussian distribution for modelling may not be sufficient and a more complex model (e.g., Gaussian mixture model) could be employed.

In some cases, for instance players 2 and 4 in Table 5.5, using more note instances has had a

Player Identification Accuracy (%)			
	Note Instances		
Note	Single	Two	Three
D_4	36	38	35
E_4	57	63	68
$F\#_4$	19	22	26
G_4	42	40	38
A_4	51	54	55
B_4	44	50	49
D_5	36	37	37
E_5	41	40	39
$F\#_5$	47	50	47

Table 5.4: Player identification accuracy (%) for all notes in folds 1-4, showing results for single, two and three note instances.

negative impact on accuracy. This is due to harmonic data from other players being much closer to the model.

Data is extracted from commercial recordings where players may have used different instruments and recordings may have been mixed with different effects processing.

The amount of training and testing data, at least for some notes, may have affected the performance. The recordings are in a range of keys and this has a bearing on the occurrences of certain notes within the tunes.

5.2.6 Discussion

Timbral variations between professional players are small but often show differences that are identifiable across a range of different notes. Players at this level often show F_1 harmonics at the same level or in excess of F_0. There are variations between harmonic levels on individual notes but at this level of playing, timbre depends on the magnitudes of the higher harmonics in comparison to the fundamental (Fletcher, 1975; Pollard, 1996).

The advantage of using commercial recordings is that they are available in the public domain but there is very little specific information with regard to room acoustics, choice of microphone or equalisation added during the recording and mixing process. These issues would be minimised by

Player Identification Accuracy (%)			
	Note Instances		
Note	Single	Two	Three
Player 1	51	58	59
Player 2	31	30	28
Player 3	49	53	55
Player 4	57	54	51
Player 5	33	35	36

Table 5.5: Player identification accuracy (%) for all notes in folds 1-4, showing results for single, two and three note instances.

using a larger dataset that incorporates multiple repetitions of each tune played by the same player to minimise the effect of different instruments and recording techniques. Recreating the tests with control over the recording process and selection of corpus would result in a study showing a more realistic comparison between players and allow for deeper study into individual players' timbral treatment of specific parts of tunes as well as discovering whether consistency exists across a variety of different tune types.

5.2.7 Conclusions

This study aimed to evaluate whether individual players could be identified from harmonic magnitudes of notes extracted from commercial recordings where the notes are played as part of a performance of Irish traditional flute playing.

Ground truth metadata was annotated to accompany the recordings, allowing note durations and pitch data to be used in the extraction of harmonic magnitudes. Cuts, strikes and breaths were excluded from the study and the central third of each note was used as the signal is steady-state. Identification took place by creating a Gaussian mixture model for each player and identification accuracy was computed over one, two and three note instances.

The study showed that timbral differences between professional players are small but they have the ability to control and manipulate higher order harmonics. Results were variable and in some cases only marginally better than chance. As the recordings already existed, no control over microphone or effects was possible. The range of melodies being played also meant that players were often presenting different playing styles due to repertoire.

In order to rectify these issues, a dataset should be collected where a number of professional players are recorded in a controlled environment playing the same melodies. As recording and then manually annotating ground truth data is a time-consuming activity, it is also important to move towards a fully automatic system. A viable first step would be to explore automatic note onset detection in the context of traditional flute playing.

5.3 Study 3: Note, cut and strike detection

In order to classify the style of a flute player, it is important to be able to reliably detect individual features such as notes, breaths and ornaments in playing of melodies. The findings of this study were published in Ali-MacLachlan et al. (2016).

A method is presented for the detection of both notes and single note ornaments known as cuts and strikes. Both ornaments generate a pitch deviation: a cut is performed by quickly lifting a finger from a tonehole then replacing it; a strike involves momentarily covering the tonehole below the note being played. The cut and strike elements of multi-note ornaments, known as short roll and long roll, are also analysed. Figure 5.11 shows the pitch deviation for cuts and strikes. Long and short rolls are also displayed, showing the inclusion of cut and strike figures. A long roll occupies the same duration as three eighth notes whereas a short roll is equivalent to two eighth notes. In practice, ITM follows a swing rhythm—while there is a regular beat, swing follows an irregular rhythm and therefore each eighth-note section may not be of equal duration in normal playing (Schuller, 1991).

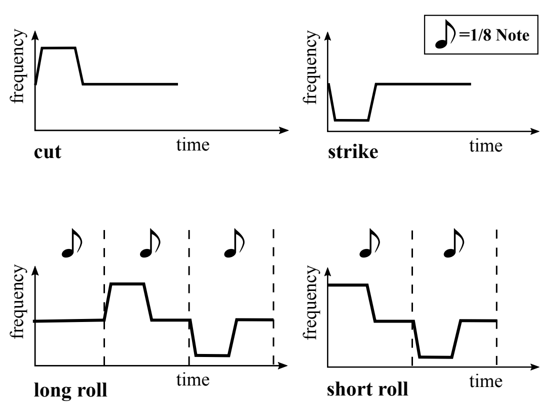


Figure 5.11: Frequency over time of *cut* and *strike* articulations showing change of pitch. *Long* and *short rolls* are also shown with pitch deviations (eighth note lengths shown for reference).

An evaluation is performed using several modern onset detection algorithms and a dataset comprised of 79 real flute performances of ITM as detailed in Appendix 3.3, in the column FMA16. A demonstration of how this information may be utilised towards the determination of notes and single note ornamentations is then provided.

5.3.1 Method

In order to create a fully automated method, onset detection is used to divide the recording into a number of segments. Event features are then extracted from inter-onset intervals (IOI). These features are used in a supervised learning algorithm to classify the segments as one of three distinct classes: notes, cuts and strikes. Figure 5.12 shows an overview of the proposed method. For onset detection, the top-performing algorithm from the evaluation presented in Section 5.3.2.2 is used. The following sections provide a discussion of the remaining feature extraction and classification stages.

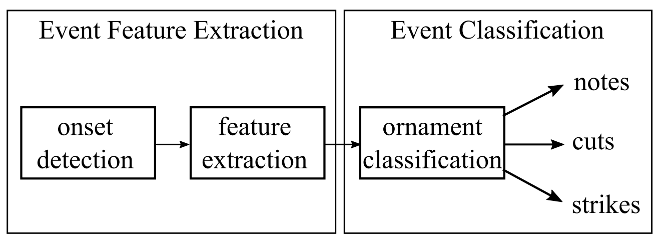


Figure 5.12: Overview of the proposed classification method of notes, cuts and strikes in flute signals. First phase shows feature extraction from segmented audio events and second phase shows classification of the events.

5.3.1.1 Feature extraction

In order to capture the differences between each event type, features are extracted relating to rhythm, timbre and pitch. An important distinction between notes, cuts and strikes is their duration, where notes are substantially longer than the two ornaments. To capture this the length ms of event segments is used. Timbral features are then extracted as these are also important in class distinction. The change in timbre is caused by player's fleeting finger motion as a tonehole is temporarily opened or closed. This results in a unique timbre that differs from notes. For that purpose 13 MFCCs are extracted, excluding the first coefficient, and 12 chroma features to accommodate for timbre and pitch changes in each of the articulations.

To extract features from the audio segments the input audio (mono WAV files) is downsampled to

Parameters	Study 3
Neural network	Feed-forward
Features	13 MFCC, 12 chroma, 1 event length (ms)
No. of hidden layers	2
No. of neurons in hidden layer	20, 20
Initialisation	Random non-zero between +/-1
Training type	Adam optimiser, learning rate 0.003
Training complete	10,000 iterations
Performance measure	Cross entropy

Table 5.6: Parameter settings for ornament detection algorithm used in Study 3.

11,025 Hz. Following the approach in Mauch and Dixon (2010) the MFCC and chroma features are calculated using a Hanning window of 1024 samples with 50% overlap. The extracted features are then normalised to the range [0,1] for every corresponding feature type. Each audio segment is assigned to its class Ω (e.g. note). An n x 26 matrix F_Ω is created, where n represents the number of segments with 26 features (i.e., MFCCs, chroma, durations).

Each F_Ω segment appears in the context of musical patterns such as rolls, shakes or just consecutive notes in the recording. To account for the rhythmic, timbral and pitch changes of each event type in the context of these patterns, the first derivatives of all features are concatenated into every F_Ω segment.

5.3.1.2 Neural network classification

Audio segments are then classified into note, cut and strike classes using a feed-forward neural network.

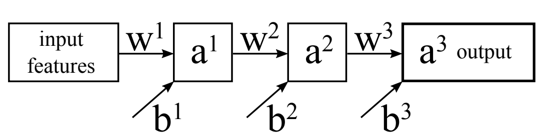


Figure 5.13: Neural network architecture containing two hidden layers a^1 and a^2, with weights w and biases b.

The proposed neural network, shown in Figure 5.13, consists of two hidden layers containing 20 neurons each. Back propagation is used to train the neural network, updating the weights and biases iteratively using scaled conjugate gradient of the output errors. A maximum iteration limit is set to 10,000 and the weights and biases are initialised with random non-zero values to ensure that training commences correctly. A validation set is used to prevent over-fitting and cross entropy is used for the performance measure. A set of parameters for the neural network are shown in Table 5.6.

The output for each layer of an L layered neural network can be calculated using:

$$a^{(l)} = f_l(a^{(l-1)}W^l + b^l), \tag{5.2}$$

where, a^l is the output at layer l and W and b are the weight and bias matrices. The transfer function is determined by the layer, as shown in Eq. 5.3.

$$f_l(x) = \begin{cases} 2/(1+e^{-2x}) - 1, & l \neq L \\ y = e^x/(\sum e^x), & l = L. \end{cases} \tag{5.3}$$

Classification is performed by finding the index of the maximum value within the output from the neural network.

5.3.2 Analysis

As the performance of the proposed method depends heavily on the accuracy of the chosen onset detection method, the aim of the first analysis is to determine the best performing onset detection algorithm. An evaluation of note and ornament classification is then performed.

5.3.2.1 Dataset

From the *ITM-Flute-99*, 79 recordings were selected (41 reels, 22 jigs, 10 polkas and 6 hornpipes). Excerpts from Larsen (2003) were omitted, as they contain tutorial recordings not representative of typical ITM performances. The tunes are detailed in Table 3.3, column FMA16.

Annotations associated with this dataset include the temporal location of onsets and the event type (e.g., note, ornament). The annotation method is described in Section 3.2.2. Additional classes such as breaths were included in the note class as they contained pitch information from a previous note.

5.3.2.2 Onset detection evaluation

In this analysis, eleven onset detection algorithms were measured for their ability to identify onsets related to notes, cuts and strikes within real-life flute recordings. Wind instrument class results from MIREX were reviewed and various studies that concerned detection of soft onsets within these instruments were examined.

Specialised methods for soft onset detection have been proposed in the literature. *SuperFlux* by Böck and Widmer (2013b) calculates the difference between two near short-time spectral magnitudes and is optimised for music signals with soft onsets and vibrato effect in string instruments. *ComplexFlux* by Böck et al. (2012b) is based on the *SuperFlux* algorithm with the addition of a local group delay measure that makes this method more robust against loudness variations of steady tones. Similarly, *LogFiltSpecFlux* introduced in Böck et al. (2012b) was designed to deal with onsets of various volume levels but was optimised for real-time scenarios.

In addition, several other onset detection methods proposed in the literature were tested. The *OnsetDetector* by Eyben et al. (2010) processes the input signal both in the forward and backward manner and outputs peaks that represent the probability of an onset at the detected position. The *Energy* (Masri, 1996), *Spectral Difference* (Foote and Uchihashi, 2001), *Spectral Flux* (Dixon, 2006) and *Kullback-Leibler* (KL) (Hainsworth and Macleod, 2003) represent detection functions solely based in the spectral domain. Brossier (2006) presented a modification to the KL algorithm shown as *Modified Kullback-Leibler* in the evaluation. The *Phase-based* method by Bello and Sandler (2003) analyses phase deviation irregularities in the phase spectrum of the signal. Lastly, the *Complex Domain* approach by Duxbury et al. (2003) combines both the energy and phase information for the production of a complex domain onset detection function. Peak-picking for the evaluated approaches is performed with *Madmom*[1] and *Aubio*[2] MIR toolboxes.

The onset detection results were calculated using the standard precision, recall and F-measure scores that measure performance of each onset detection algorithm. Precision and recall are determined from the detected flute onsets if reported within 25 ms on either side of the ground truth onset times. The mean F-measure is calculated by averaging F-measures across recordings.

5.3.2.3 Note and ornament classification evaluation

To assess the performance of the presented note and ornament classification method, two evaluations were performed using the dataset described in Section 3.2. In the first evaluation, an attempt is made to determine the worth of the chosen classification method and selected features alone. In this experiment, the manually annotated note onsets are used to segment the audio prior to the feature extraction and classification stages. In the second evaluation, a fully automated ornament detection approach is proposed. This approach relies on onset detection for segmentation. In this evaluation, the top-performing onset detection algorithm found in the onset detection evaluation (see Section 5.3.2.2)

[1] https://github.com/CPJKU/madmom
[2] http://aubio.org/

is employed. For the training of the automated method only the true positive onsets are used to ensure that the neural network is trained with the features corresponding to their correct classes.

The data is presented as seven different feature classes: (1) note; (2) cut; (3) strike; (4) breath; (5) cut at start of short roll; (6) note at start of long roll; and (7) note at start of crann.

To ensure an approximately equal proportion of training examples per class, the number of notes per recording was reduced to 6%, cuts to 30% and all strikes were left in due to the proportion of these classes in the dataset. The classification evaluation is then performed using 5-fold cross validation.

5.3.3 Results

5.3.3.1 Onset detection results

The results of the experiment are shown in Table 5.7. Evaluation of onset detection algorithms is discussed in Section 4.2.5. The *OnsetDetector* method by Eyben et al. (2010) achieves the highest precision of 83% and F-measure of 79%. The high performance of this approach is in agreement with the results in the literature for the wind instrument class (Böck and Widmer, 2013a; Böck and Widmer, 2013b). While *Spectral Flux* achieved the highest recall score of 76% this is likely due to its overestimation of the onset positions thus resulting in a lower precision value. Consequently, in note, cut and strike detection, the onsets detected using the *OnsetDetector* were used as it outperforms other tested methods.

5.3.3.2 Note and ornament classification results

A confusion matrix for note, cut and strike classification using features extracted from the annotated onset boundaries is presented in Table 5.8. The results demonstrate the effectiveness of the classification method for all three classes with 86% note, 70% cut and 74% strike detection accuracies. Misclassified notes are equally distributed across the other two classes demonstrating large timbral, pitch and rhythmic differences between note and ornament event types. The cuts and strikes are mostly misclassified as each other, which reflects their similar duration. These findings confirm the importance of duration in identifying the difference between ornaments (Gainza et al., 2004b).

The results for a fully automated system evaluation are presented in Table 5.9. Here cuts and strikes were overwhelmingly misclassified as notes. These poor results could be influenced by the imbalance between the number of annotated onsets and detected onsets. The evaluation using annotated onsets used 916 notes, 670 cuts and 672 strikes, while the fully automated method used only 691 notes, 503 cuts and 518 strikes.

	P	R	F
`OnsetDetector2015` Eyben et al., 2010	**0.8306**	0.7510	**0.7875**
`ComplexFlux2015` Böck and Widmer, 2013a	0.7414	0.6639	0.6996
`SuperFlux2015` Böck and Widmer, 2013b	0.7659	0.6714	0.7144
`LogFiltSpecFlux2015` Böck et al., 2012b	0.7597	0.6494	0.6989
`Energy` Masri, 1996	0.6870	0.5888	0.6270
`Complex Domain` Duxbury et al., 2003	0.7548	0.6561	0.6999
`Phase-based` Bello and Sandler, 2003	0.7206	0.5522	0.6177
`Spectral Difference` Foote and Uchihashi, 2001	0.7087	0.5928	0.6416
`Kullback-Leibler` Hainsworth and Macleod, 2003	0.7926	0.4025	0.5265
`Modified Kullback-Leibler` Brossier, 2006	0.7659	0.1868	0.2890
`Spectral Flux` Dixon, 2006	0.5854	**0.7618**	0.6580

Table 5.7: Precision (P), recall (R) and F-measure (F) for eleven onset detection methods. Maximum values for precision, R recall and F-measure shown in bold.

class	notes	cuts	strikes
notes	86.97	8.43	8.54
cuts	6.79	70.46	16.96
strikes	6.24	21.07	74.49

Table 5.8: Confusion matrix for classification of notes, cuts and strikes using manually annotated onsets.

class	notes	cuts	strikes
notes	81.57	83.46	82.61
cuts	6.97	6.85	6.48
strikes	11.47	9.70	10.91

Table 5.9: Confusion matrix for classification of notes, cuts and strikes using a fully automated segmentation.

Training the system with features extracted from annotated segments and testing on automatically found segments did not improve on these results. To investigate the possible reasons for the poor classification results in Table 5.9, additional analysis of the onset detection results per event type was conducted.

5.3.3.3 Note, cut and strike onset detection accuracy

Cuts and strikes are components in multi-note ornaments such as rolls and shakes. To determine where onset detection errors occur, detection accuracy is evaluated in relation to events that occurred immediately before and after the detected events. This evaluation makes it possible to determine which event classes are most difficult to detect, and provide insight in the limitations of the real-life application of the proposed method for note, cut and strike detection.

In Table 5.10, onset detection results for each class of musical pattern are presented. The classes consist of three event types where the central event is identified in bold. For example, *note **cut** note* is a detected cut with a note before and note afterwards, which exists within the event context of short and long roll or a single cut. The number of correctly detected onsets (true positives) is found as a percentage of the overall number of annotated onsets of that pattern.

As can be seen in Table 5.10, low accuracies were found for notes following ornaments. The largest error was found in the *cut **note** note*. This pattern exists only in the context of single cuts and shakes and occurred 1579 times with only 574 correctly found instances. Other patterns with cuts and strikes before notes also exhibit poor performance.

The proposed note, cut and strike detection method depends upon features extracted from the found inter-onset intervals. The events corresponding to the cut and strike classes are detected with 83% and 82% accuracies respectively. Detecting notes that exist directly after these ornaments in the onset detection stage augments the content of the features describing the ornament event types. This results in training data that does not represent the classes intended to be captured.

5.3.4 Conclusions

In this study a note, cut and strike detection method for traditional Irish flute recordings is presented. The chosen approach to this problem is that of inter-onset segment classification using feed-forward neural networks. To evaluate the effectiveness of this approach an evaluation of various onset detection algorithms was conducted on 79 recordings collected as part of the *ITM-Flute-99* dataset. This method is designed to be the first step in the development of an automatic feature extraction system.

When using ground truth onset annotations, 86%, 70% and 74% accuracies were achieved for note, cut and strike classification respectively. Using automatically detected onsets to train the neural network gave poor classification results. Analysis of the detected onsets and the context in which they appear was performed to establish both the degree of the errors and the musical patterns in which they occur.

It is important to continue work on improving the automated detection of note events and classification of ornaments. As the context of the event is important in its classification, methods with additional features and other neural network architectures (e.g., recurrent neural networks, networks with long short-term memory) will be utilised in order to capture trends that appear in time-series data.

Musical pattern			Event context	Accuracy	True positives	Total onsets
note	**note**	note	*single notes*	83.36	8651	10378
note	**cut**	note	*short & long rolls & single cuts*	83.44	1870	2241
note	**note**	cut	*notes before a roll*	84.16	1637	1945
cut	**note**	note	*notes after single cuts & shakes*	36.35	574	1579
note	**strike**	note	*short & long rolls & single strikes*	82.39	552	670
cut	**note**	strike	*short & long rolls*	34.62	180	520
strike	**note**	note	*last notes in rolls*	16.22	84	518
cut	**note**	cut	*shakes*	31.03	45	145
strike	**note**	cut	*last notes in rolls*	20.69	30	145
note	**note**	strike	*notes before single strikes*	90.85	129	142

Table 5.10: Onset detection results for each event class (bold) in context of events happening before and after detected onset. Accuracy shown as percentage of accurately detected onsets (true positives) from that pattern.

5.4 Study 4: Improved onset detection for ITM using deep learning

The approach undertaken in this study extends upon the work presented in Study 3 (Section 5.3), where onsets were detected through the use of the `OnsetDetector` system (Eyben et al., 2010) and inter-onset segment classification was performed using a classification method based on a feed-forward neural network. The `OnsetDetector` system was trained on a broad range of music making it effective at detecting a variety of instrument onsets. While note onset detection accuracy was very successful, ornament detection accuracies proved to be quite low by comparison.

In an attempt to improve onset detection for ITM, an onset detection method based on a CNN was implemented. The model was trained specifically on ITM flute recordings. The pictorial nature of training data means that the system is trained on a representation of pitch and dynamics over time. The earlier study showed that detection of ornament onsets is context-dependent and in this study detection accuracy is evaluated in relation to events that occur immediately before and after the detected events. In this evaluation, the position and context of onset detection errors can be determined. This allows limitations in the detection of notes, cuts, strikes and breaths to be observed in the context of traditional flute music being played at a professional level.

Breaths and the cut and strike elements of multi-note ornaments known as *short roll*, *long roll*, *crann* and *single trill* are also evaluated (Larsen, 2003). Figure 5.14 depicts single-note and multi-note ornaments over time.

Onset detection algorithms are used to identify the start of musically relevant events. Ornament onset detection for Irish traditional flute recordings is a difficult task due to their subtle nature; ornaments are often played in a short and soft manner, resulting in onsets characterised by a long attack with a slow energy rise (Gainza et al., 2005; Böck and Widmer, 2013a).

5.4.1 Method

The onset detection method in this study is based on a CNN deep learning classification method. CNNs share weights by implementing the same function on sub-regions of the input. This enables CNNs to process a greater number of features at a lower computational requirement compared to other neural network architectures (i.e., multi-layer perceptron). High onset detection accuracies have been achieved by CNNs using larger input features (Schlüter and Böck, 2014).

CNNs are feed-forward neural networks containing convolutional layers. Feature maps are obtained by using a filter kernel to convolve the output of the layer below. In comparison to a fully connected

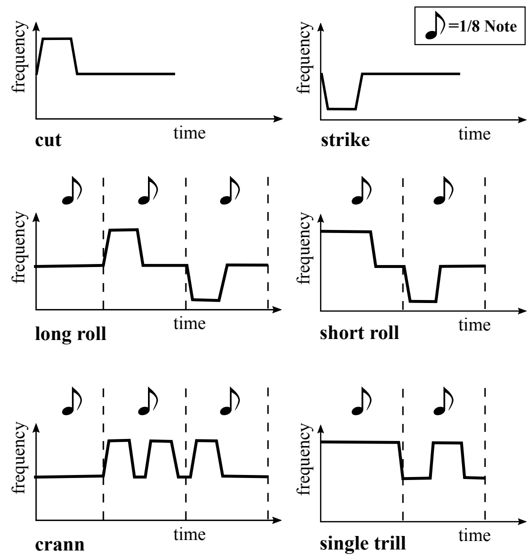


Figure 5.14: Frequency over time of *cut* and *strike* articulations showing change of pitch. *Long* and *short rolls*, *cranns* and *single trills* are also shown with pitch deviations. Eighth-note lengths are shown for reference.

layer, a feature map represents the layout of the input data but has far less trainable parameters allowing for more efficient computation.

The output h of a two-dimensional convolutional layer of dimensions I and J, with a rectified linear unit transfer function is calculated using:

$$h_{ij}^{f} = r\left(\sum_{l=0}^{L-1}\sum_{m=0}^{M-1} W_{ml}^{f} x_{(i+l)(j+m)} + b^{f}\right), \tag{5.4}$$

where x is the input features, W and b are the shared weights and bias and f is the index to the feature map. L and M are the dimensions of the shared weight matrix. The equation for the rectifier linear unit transfer function r is:

$$r(\phi) = max(0, \phi). \tag{5.5}$$

The output of the convolutional layer h is processed using a max pooling layer which results in a $\frac{I}{a}$ by $\frac{J}{b}$ output where a and b are the dimensions of the sub-regions processed. Pooling layers are used to subsample or shrink the input image in order to increase processing efficiency. In a max pooling layer the data is reduced by selecting only the maximum value in each filter (Géron, 2017).

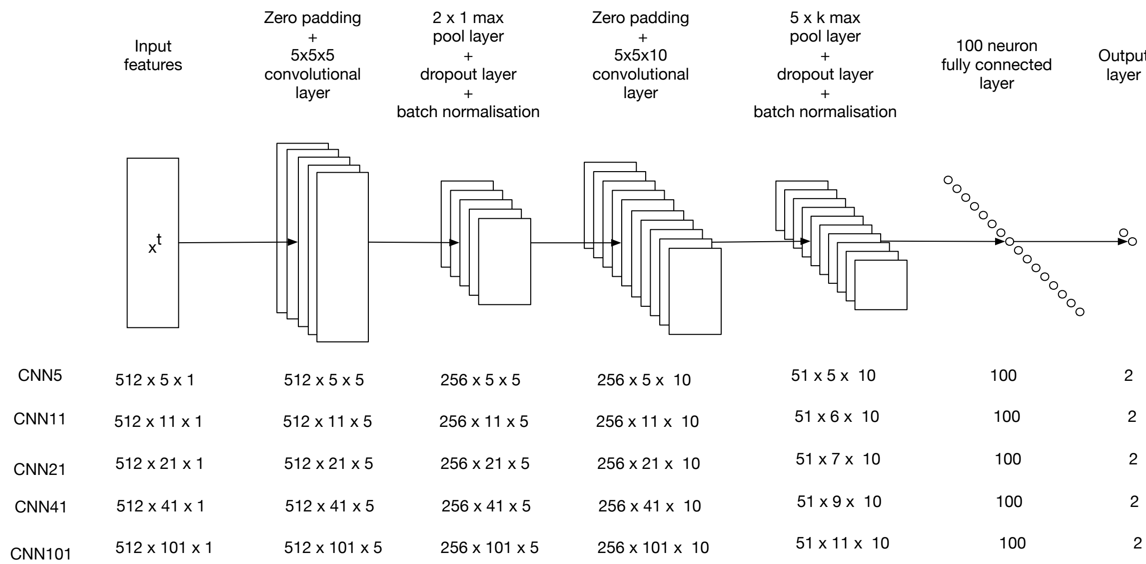


Figure 5.15: Overview of proposed implemented CNN system with different input feature sizes.

In order to prevent overfitting, where the function is trained too closely to the data, at every training step each neuron apart from the output neurons has a probability of being excluded or dropped from the calculation. The rate of probability is known as the dropout rate (Hinton et al., 2012; Srivastava et al., 2014)

Batch normalisation is used in order to minimise problems caused by vanishing or exploding gradients, or issues caused by the inputs of each layer changing during training as the parameters of the previous layers are altered. This is achieved by adding an operation before the activation function of each layer to firstly zero-centre and normalise the inputs, and then apply scaling and shifting in order that the model can learn the optimal mean and range for each layer (Ioffe and Szegedy, 2015).

A fully-connected layer consists of neurons that are linked to all of the neurons in previous and future layers. The output Y of a fully connected layer with a rectified linear unit transfer function is calculated using:

$$Y = r(W_c z + b_c), \tag{5.6}$$

where z is the input, W_c is the weight matrix and b_c is the bias for output layer c. For the softmax output layer the rectified linear unit r transfer function is swapped for the softmax function, allowing the network to support multiple class outputs to add up to 1. It is calculated using:

$$softmax(\phi) = \frac{e^{\phi}}{\sum e^{\phi}}. \tag{5.7}$$

In classification tasks, the output of the CNN is derived from a fully connected layer that brings together data from all feature maps and is designed to have the desired number of outputs (Schlüter and Böck, 2013; Schlüter and Böck, 2014). This could be a binary problem where the answer is yes or no, or a multiple-class problem where the network is trained to identify a number of different possible inputs.

Figure 5.15 gives an overview of the implemented CNN architecture. The input features are first fed into two sets of convolutional and max pooling layers containing dropouts and batch normalisation. The output is then reshaped into a one-dimensional format before being run through a fully-connected layer and a softmax output layer.

The CNN was implemented using the Tensorflow Python library (Abadi et al., 2016) with training data consisting of target activation functions created from ground truth annotations of tracks in the *ITM-Flute-99* dataset. A frame-based approach was taken where each frame is assigned 1 if it contains an onset or 0 if it does not.

5.4.1.1 Input features

Before processing by the CNN, the audio files must be segmented into frame-wise spectral features. An N sample length audio file was segmented into T frames using a Hanning window of γ samples ($\gamma = 1024$) and a hop size of $\frac{\gamma}{2}$. A frequency representation of each of the frames was then created using the discrete Fourier transform resulting in a $\frac{\gamma}{2}$ by T spectrogram.

As classification is performed on the frame at the centre of the input features, a potentially crucial parameter is the number of input frames ψ. To determine the most efficient number of frames to use as the input for the CNN, five different values for ψ were used ($\psi = [5, 11, 21, 41, 101]$) creating the `CNN5`, `CNN11`, `CNN21`, `CNN41`, `CNN101` versions respectively.

5.4.1.2 Layer sizes

The layer sizes used for the different input features are indicated at the bottom of Figure 5.15. The size of all layers are consistent across systems apart from the second dimension k of the second max pooling layer. k is set to 1, 2, 3, 5 and 10 for the different input features sizes respectively.

Parameters	**Study 4**
Neural network	Convolutional Neural Network
Features	13 MFCC, Spectrogram 512 x T frames
Layers	2 x (convolutional, max pool, dropout), fully connected layer
Blocks	Block A: 5 x 512 x n (no. of frames), Block B: 10 x 256 x n
Initialisation	Random non-zero between +/-1
Training type	Adam optimiser, learning rate 0.003
Training complete	Validation set accuracy does not increase
Performance measure	Cross entropy
Mini batch	1000 frame
Dropout probability	0.25
Frame options	5 different total number of frames (n): 5, 11, 21, 41, 101

Table 5.11: Parameter settings for onset detection algorithm used in Study 4.

5.4.1.3 Peak picking

The onsets must be temporally located from within the activation function Y output from the CNN. To calculate onset positions, the method from Southall et al. (2016) is used. A threshold τ is first determined using the mean across all frames and a constant λ:

$$\tau = \lambda \bar{Y}. \tag{5.8}$$

The current frame t is determined to be an onset if its magnitude is greater than those of the surrounding two frames and above threshold τ.

$$O(t) = \begin{cases} 1, & y^t = max(y^{t-1:t+1}) \ \& \ y^t > \tau, \\ 0, & otherwise. \end{cases} \tag{5.9}$$

Finally, if an onset occurs within $25ms$ seconds of another then it is removed. This threshold was chosen by analysing the lengths of strikes, typically the shortest ornament class.

5.4.1.4 Training

The training data is divided into 1000 frame mini-batches consisting of a randomised combination of 100 frame regions from the feature matrix. The Adam optimiser (Kingma and Ba, 2014) is used to train the neural networks with an initial learning rate of 0.003. Training is stopped when the validation

Player	Album(s)	Reels	Jigs	Polkas	Hornpipes
Harry Bradley	The First of May	8	4		4
Bernard Flaherty	Flute Players of Roscommon Vol.1	2			
John Kelly	Flute Players of Roscommon Vol.1		1		1
Josie McDermott	Darby's Farewell	2	2		2
Catherine McEvoy	Flute Players of Roscommon Vol.1, Traditional Flute Playing in the Sligo-Roscommon Style	4			
Matt Molloy	Matt Molloy, Heathery Breeze, Shadows on Stone	5	2		
Conal O'Grada	Cnoc Bui	13	1	10	
Seamus Tansey	Field Recordings	4			
Michael Tubridy	The Eagle's Whistle	2	9		
John Wynne	Flute Players of Roscommon Vol.1		3		

Table 5.12: Dataset recordings showing player, album source and tune type.

set accuracy does not increase between iterations. To ensure training commences correctly, the weights and biases are initialised to random non-zero values between ± 1 with zero mean and standard deviation equal to one. The performance measure used is cross entropy and the dropout probability d is set to 0.25 during training. Parameter settings for the neural network are shown in Table 5.11.

5.4.2 Analysis

As the performance of the proposed method depends heavily on the accuracy of the chosen onset detection method, the aim of the first evaluation is to determine the quality of existing timing data. An evaluation is performed on the onset detection method by comparing it against the most successful method found in Study 3. The performance of the system is then assessed for notes and ornament detection and the worth of generalised versus flute-specific training data is measured.

5.4.2.1 Dataset

The corpus for analysis consists of 79 solo flute recordings from the *ITM-Flute-99* corpus and is discussed in Section 3.2. Players, tune type and recording sources are detailed in Table 5.12. Individual tune titles are contained in Appendix 3.3, column FMA 2017.

The dataset contains annotations for onset timing information and labels for notes, cuts, strikes and breaths, and contains approximately 18,000 individual events. First notes of long rolls, short rolls and cranns are also identified and labelled.

Event labels are applied as follows: 1, note; 2, cut; 3, strike; 4, breath; 5, cut - start of short roll; 6, note–start of long roll; 7, note–start of crann. Three-note sequences are labelled with the central event as the first number, the preceding event as the second number and the following event as the third number. 411 is *note* ***breath*** *note* - two notes separated by a breath and 115 is *note* ***note*** *cut* - two notes before the start of a short roll.

5.4.2.2 Onset detection evaluation

The ground truth annotation process was completed using multiple tools as the project evolved resulting in inconsistencies being found in onset placement and labelling. The quality of these annotations was improved by comparing ground truth onsets against true positive and false negative onsets obtained using `OnsetDetector` (Eyben et al., 2010). Events outside a 50ms window of acceptance were evaluated by an experienced flute player, allowing events to be checked for onset accuracy. Patterns containing impossible sequences of events were also identified and eliminated by checking each event in context with previous and subsequent events. An example of this is a roll that uses notes from both octaves.

To obtain the results for the `OnsetDetector` system on the updated dataset all tracks are processed with the output onset times compared against the annotated ground truth. The accuracy relating to the `OnsetDetector` method is assessed before and after annotation correction and the number of spectrogram frames used as input.

The `OnsetDetector` system is then evaluated against the implemented CNN systems. The dataset is divided by tracks into a 70% training set (55 tracks), 15% validation set (12 tracks) and 15% test set (12 tracks). The training set is used to train the five versions of the CNN (`CNN5`, `CNN11`, `CNN21`, `CNN41` and `CNN101`) onset detector using the different input feature sizes, the validation set is used to prevent over-fitting and the test set is used as the unseen test data. The `OnsetDetector` results for the 12 test tracks are compared to the results from the 5 CNN versions. F-measure, precision and recall are used as the evaluation metrics with onsets being accepted as true positives if they fall within 25ms of the ground truth annotations.

5.4.3 Results

5.4.3.1 Onset detection results

	P	R	F
`OnsetDetector` Before annotation improvement	83.06	75.10	78.75
`OnsetDetector` After annotation correction	85.86	78.46	81.85
`CNN5`	87.06	84.71	85.73
`CNN11`	88.07	84.73	86.25
`CNN21`	88.82	**88.26**	**88.46**
`CNN41`	**88.84**	86.63	87.58
`CNN101`	88.72	86.21	87.32

Table 5.13: Precision (P), Recall (R) and F-measure (F) for `OnsetDetector` (Eyben et al., 2010) before and after annotation improvement, `CNN5`, `CNN11`, `CNN21`, `CNN41`, and `CNN101`.

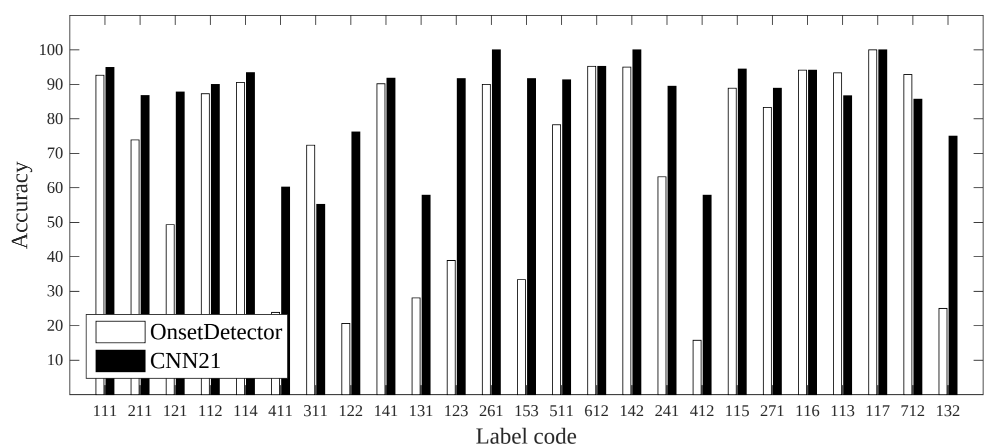


Figure 5.16: Accuracy of `OnsetDetector` and `CNN21` onset detectors for each event class above 10 onsets.

Table 5.13 presents the overall precision, recall and F-measure performance for the `OnsetDetector` and five CNN versions. The results indicate that all versions of the CNN achieve higher results than the `OnsetDetector`. The `CNN21`, which uses 10 spectrogram frames prior and subsequent to the middle frame achieves the highest recall and F-measure. The `CNN41` achieves a slightly higher precision than

			True Positives		
Label Code	Musical Pattern	Event Context	Onset Detector	CNN21	Total
111	note **note** note	*single notes*	1097	1124	1184
211	note **cut** note	*single cuts*	229	269	310
121	cut **note** note	*single cuts*	133	237	270
112	note **note** cut	*single cuts*	192	198	220
114	note **note** breath	*single notes*	96	99	106
411	note **breath** note	***single notes with breath***	21	53	88
311	note **strike** note	***single strike, end of roll***	55	42	76
122	cut **note** cut	*trill*	13	48	63
141	breath **note** note	*single notes*	55	56	61
131	strike **note** note	***single strike, end of roll***	16	33	57
123	cut **note** strike	*rolls*	14	33	36
261	note **cut** note	*start of long roll*	27	30	30
153	cut **note** strike	*start of short roll*	8	22	24
511	note **cut** note	*note before start of short roll*	18	21	23
612	note **note** cut	*note before start of long roll*	20	20	21
142	breath **note** cut	*breath before single cut*	19	20	20
241	breath **cut** note	*breath before single cut*	12	17	19
412	note **breath** cut	***breath before single cut***	3	11	19
115	note **note** cut	*two notes before start of short roll*	16	17	18
271	note **cut** note	*start of crann*	15	16	18
116	note **note** note	*two notes before start of long roll*	16	16	17
113	note **note** strike	*single strike*	14	13	15
117	note **note** note	*two notes before start of crann*	14	14	14
712	note **note** cut	*note before start of crann*	13	12	14
132	strike **note** cut	*cut after roll*	3	9	12

Table 5.14: Results comparing `OnsetDetector` and `CNN21` onset detectors for all event classes in context of events happening prior and subsequent to detected onset. Label codes of patterns with under 70% accuracy for `CNN21` shown in bold. Patterns with under 10 total onsets omitted.

	Notes	Cuts	Strikes	Breaths
`OnsetDetector`	76.31	77.78	72.37	19.83
`CNN21`	89.57	91.29	55.26	59.06

Table 5.15: Accuracy (%) of `OnsetDetector` and `CNN21` onset detectors for note, cut, strike and breath classes above 10 onsets.

the `CNN21`, however achieves lower recall accuracy. The performance across the five CNN versions is fairly similar, illustrating that the moderate to higher values for the ψ parameter ($\psi = [21, 41, 101]$) are most appropriate for the task. The high performance of this approach is likely due to two factors. First, as CNNs are capable of processing large input feature sizes, they incorporate more context into the detection of a single frame. Second, as the CNNs are trained solely on traditional flute signals there is less variation in the represented classes, which has the potential of improving accuracy.

5.4.3.2 Note, cut and strike onset detection accuracy

The onset detection results for each class of musical pattern with over 10 onsets in the test corpus of 12 tunes are presented in Table 5.14. The mean pattern precision across all classes was 79.22 for `CNN21` in comparison with 59.86 for `OnsetDetector`.

The classes consist of three event types where the central event is identified in bold. For example, label code 211 (*note* ***cut*** *note*) is a detected cut with a note before it and note after it, which exists within the event context of short and long roll or a single cut. The number of correctly detected onsets (true positives) is found as a percentage of the overall number of annotated onsets of that pattern. Label codes with an accuracy of less that 70% are shown in bold.

As can be seen in Figure 5.16 and Table 5.14, low accuracies were found for strikes and notes following strikes. As a strike is played by momentarily tapping a finger over a tonehole, the pitch deviation is often much smaller than that of a cut and the event time is often shorter, making it more difficult to detect. Breaths are also difficult to detect in commercial recordings because it is usual to apply a generous amount of reverb effect at the mixing stage, resulting in a slow release masking a defined offset. Table 5.15 further illustrates inaccuracies in the detection of strikes and breaths by showing the accuracy for each single event class - note, cut, strike and breath. The note class also includes the notes at the start of ornaments such as long roll and crann and the cut class includes cuts at the start of short rolls.

5.4.3.3 Generalised and specific training data

`OnsetDetector` is a leading generalised note onset detector trained on a wide range of musical signals whereas `CNN21` is specifically trained on the solo flute data contained in the *ITM-Flute-99* dataset. In order to explore the effectiveness of using specifically-trained neural networks for onset detection, `CNN21` was trained with both `OnsetDetector` and *ITM-Flute-99* datasets and these are compared to `OnsetDetector`, trained on its own dataset. As can be seen in Figure 5.17 and Table 5.16, `CNN21` trained on solo flute signals is more accurate in 18 of a total of 22 classes, representing 82% of the classes. The accuracy of `CNN21` trained on *ITM-Flute-99* shows a marked improvement on the accuracies of the two other methods in a number of classes. Mean accuracies are: `CNN21` trained on `OnsetDetector` dataset - 66.99, `CNN21` trained on *ITM-Flute-99* dataset - 84.62 and `OnsetDetector` trained on `OnsetDetector` dataset - 65.44.

Classes with 1 as the first digit represent notes surrounded by other features. 122 (*cut* ***note*** *cut*) is typical of a class where quick pitch deviations on either side would make it more difficult for a generalised method to detect the note. 132 (*strike* ***note*** *cut*) is more difficult because the pitch deviation created with a strike is very quick and the frequency will may not change substantially. Notable improvements are also made in 411 (*note* ***breath*** *note*) and 412 (*note* ***breath*** *cut*). A breath in this context is not silent and there may be a reverb tail from the cut or other activity occurring before the pattern commences. As the *ITM-Flute-99* dataset includes breaths as a feature class, training `CNN21` with this data substantially improves detection in these classes.

5.4.4 Conclusions

In this study, a convolutional neural network (CNN) based onset detection method trained solely on Irish flute recordings is presented. The results from the evaluation show that this method outperformed the existing state-of-the-art generalised trained `OnsetDetector`. The annotations of the *ITM-Flute-99* dataset were improved in accuracy by employing a process of automatic onset detection followed by manual correction as required. To evaluate the effectiveness of this approach, the top performing CNN version (CNN21) method is compared to the `OnsetDetector` by Eyben et al. (2010), the most successful method found in Ali-MacLachlan et al. (2016).

In future research, it is important to collect a controlled corpus of recordings. The existing *ITM-Flute-99* dataset has several limitations. Players do not play the same melodies and there is no control over microphone or effects such as reverberation on recordings. A new corpus would be used to further develop player identification using deep learning techniques.

		Accuracy		
Label Code	Musical Pattern	CNN21 trained on Onset Detector dataset	CNN21 trained on *ITM-Flute-99* dataset	Onset Detector trained on Onset Detector dataset
111	*note* ***note*** *note*	88.76	**94.93**	92.65
211	*note* ***cut*** *note*	83.10	**86.77**	73.87
121	*cut* ***note*** *note*	37.19	**87.78**	49.26
112	*note* ***note*** *cut*	82.76	**90.00**	87.27
311	*note* ***strike*** *note*	**84.57**	55.26	72.37
131	*strike* ***note*** *note*	23.21	**57.89**	28.07
114	*note* ***note*** *breath*	86.27	**93.40**	90.57
123	*cut* ***note*** *strike*	45.45	**91.67**	38.89
411	*note* ***breath*** *note*	22.45	**60.23**	23.86
261	*note* ***cut*** *note*	82.35	**100.00**	90.00
141	*breath* ***note*** *note*	91.04	**91.80**	90.16
612	*note* ***note*** *cut*	87.27	**95.24**	**95.24**
153	*cut* ***note*** *strike*	42.86	**91.67**	33.33
511	*note* ***cut*** *note*	87.76	**91.30**	78.26
115	*note* ***note*** *cut*	91.49	**94.44**	88.89
116	*note* ***note*** *note*	88.37	**94.12**	**94.12**
132	*strike* ***note*** *cut*	10.53	**75.00**	25.00
113	*note* ***note*** *strike*	**96.67**	86.67	93.33
122	*cut* ***note*** *cut*	20.83	**76.19**	20.63
142	*breath* ***note*** *cut*	95.83	**100.00**	95.00
241	*breath* ***cut*** *note*	25.00	**89.47**	63.16
412	*note* ***breath*** *cut*	**100.00**	57.89	15.79

Table 5.16: Accuracy of `OnsetDetector` and `CNN21` trained on `OnsetDetector` and *ITM-Flute-99* datasets. Onset detection results for each event class (bold) in context of events happening before and after the detected onset. Accuracy shown as percentage of accurately detected onsets (true positives) from that pattern. Mean accuracies are 66.99%, 84.62% and 65.44% respectively.

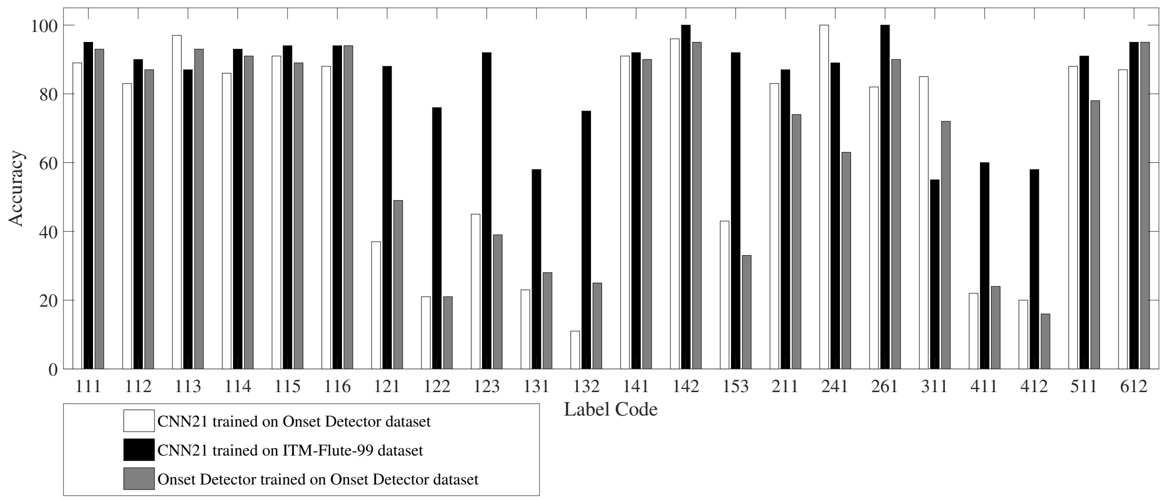


Figure 5.17: Accuracy of `OnsetDetector` and `CNN21`trained on `OnsetDetector` and *ITM-Flute-99* datasets.

5.5 Study 5: Player identification using deep learning

In order to determine stylistic differences between players, an important step is to develop methods to recognise different players in audio signals. Study 2 relied on the Gaussian Mixture Model and returned identification accuracies that were lower than expected.

In this study, convolutional neural networks (CNN) were used as they had proved successful in identification of speakers from vocal recordings (Paradisi et al., 2017). The use of deep learning, in particular CNN, is an important step in more accurate player identification. In order to identify flute players in ITM, a CNN system is proposed in order to make use of their ability to efficiently process large datasets.

Study 2 also relied upon a corpus of recordings where musicians do not play the same pieces of music and there is little information about recording equipment or effects used in mixing the tracks. The methodology used to manually annotate the 20 tunes analysed in Study 2 was extended to a total of 99 tunes and the full dataset is named *ITM-Flute-99*.

In order to extend the experimentation based on the findings of the study detailed in Section 5.2, a new dataset named *ITM-Flute-Style6* was collected to address the limitations found in *ITM-Flute-99*. Six professional concert flute players with a background in ITM were chosen and each played the same tunes from a predetermined corpus offering a range of typical modes and rhythms, as shown in Table 3.5.

The audio segments, described in Section 5.5.1.1, are used to evaluate player recognition accuracy. There are a total of 1885 segments comprising of 1438 from *ITM-Flute-Style6* and 447 from *ITM-Flute-79*. This translates to approximately 2 hours of recordings from *ITM-Flute-Style6* and 40 minutes of recordings from *ITM-Flute-79*.

5.5.1 Method

A deep learning model is used to classify musician-specific features for the task of player recognition. First, the audio waveforms are pre-processed to create a desired signal representation in a form of MFCCs. Then the signal is split into 5-second segments that represent different timbral and rhythmic characteristics of each performer. Given these characteristics, the model aims to recognise the player of previously unseen audio segments. The next subsections discuss the single blocks of the system in more detail.

5.5.1.1 Feature extraction

First, a downsampled 22.05 kHz 16-bit mono audio signal is split into five second segments. These audio segments offer enough information to capture rhythm patterns as well as result in a large number of observations. A magnitude spectrogram is then calculated using a 1024-sample window size and a resulting frame rate of 100 Hz. Finally, the frequency bins are transformed into 40 MFCCs in a frequency range from 32 Hz to 4,000 Hz as shown in Figure 5.18.

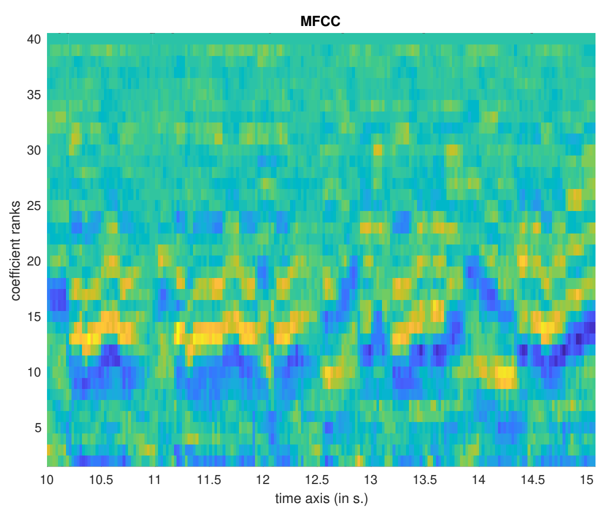


Figure 5.18: 5-second MFCC representation (40 coefficients) of an excerpt of *ITM-Flute-Style6* Player 1, Cooley's Reel.

Parameters	**Study 5**
Neural network	Convolutional Neural Network
Features	40 band MFCC
Layers	2 x (convolutional, max pool, dropout), fully connected layer
Blocks	Block A: 10x5x5, Block B: 20x5x5
Initialisation	Random non-zero between +/-1
Training type	Adam optimiser, learning rate 0.003
Training complete	50 epochs commenced, validation set cost starts to increase
Performance measure	Cross entropy
Mini batch	1000 frame
Dropout probability	0.25

Table 5.17: Parameter settings for player identification algorithm used in Study 5.

5.5.1.2 Architecture

Figure 5.19 gives an overview of the implemented CNN architecture. The convolutional layers are constructed using two different building blocks that process the input features: Block A consists of a layer with 10 5x5 filters and block B consists of a layer with 20 5x5 filters; both are followed by max pooling, dropout layers (Srivastava et al., 2014) and batch normalisation (Ioffe and Szegedy, 2015). A fully connected layer with 100 neurons and a softmax output layer of size c (number of player classes) follows the convolutional blocks. Parameters for the neural network are shown in Table 5.17.

The Adam optimiser (Kingma and Ba, 2014) is used with a learning rate of 0.003 to train the model. Stochastic gradient descent is performed (batch size = 250) with the cross entropy loss function. Training is stopped when two criteria have been met: 1) 50 epochs have commenced and 2) validation set cost starts to increase between epochs. The weights are initialised using a scaled uniform distribution (Sussillo, 2014) and biases are initialised to zero.

5.5.2 Analysis

The proposed method of player recognition relies on the accuracy of recordings in representing the playing style of each musician. In order to assess the ability of the proposed system to recognise different players, four evaluation strategies are implemented utilising 5-second audio segments from the collected recordings.

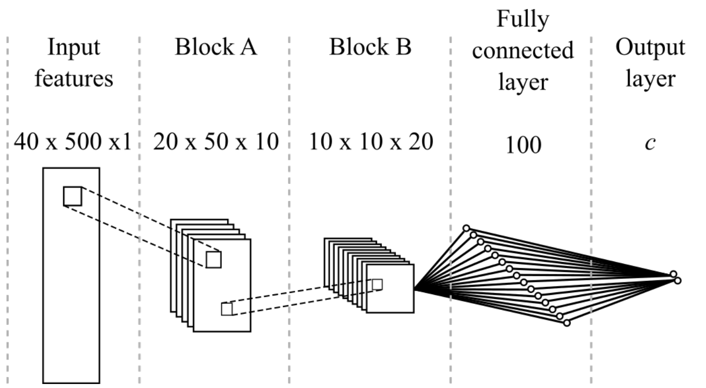


Figure 5.19: Overview of the proposed CNN. The input data flows between different network layers from left to right. The input data size at each computational block is presented above each layer.

5.5.3 Evaluation strategies

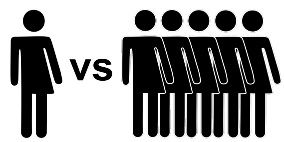
Four different evaluation strategies are implemented, consisting of two player recognition approaches (`2-class` and `Multi-class`) and two contexts (`Simplified` and `Realistic`) to test the system performance. An overview of the strategies is given in Figure 5.20. It is expected that the `Realistic`context will return lower accuracies as the larger dataset is representative of a wider range of player styles.

5.5.3.1 Simplified 2-class

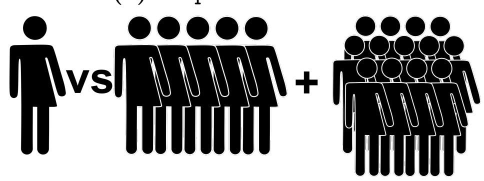
In the first evaluation strategy, termed `Simplified 2-class` a `2-class` approach (using a softmax output layer with 2 neurons, $c=2$) is used to identify a single player from a mixed corpus. The first class (1) corresponds to the observed player and the second class (0) represents all other players. Due to there being only 6 players, the difference in total class observations should not cause significant bias during training. The `2-class` approach in a `Simplified` case is tested using just the 6 player data from *ITM-Flute-Style6*. All recording variations of six tracks are used for training and all recording variations of the other two tracks are split evenly into validation and test sets. Four fold cross validation is performed so that each track appears in the test set. This is repeated 6 times with the player class corresponding to a different player each time.

5.5.3.2 Realistic 2-class

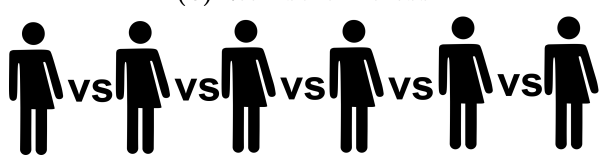
In the second evaluation strategy, termed `Realistic 2-class`, the same `2-class` approach is used as in Section 5.5.3.1 but includes *ITM-Flute-79* to create a more realistic evaluation. It is expected that the inclusion of the additional data will reduce performance. All tracks from the added dataset are



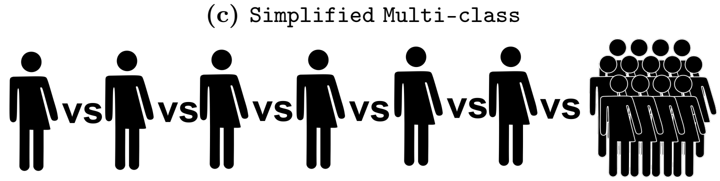
(a) `Simplified` `2-class`



(b) `Realistic` `2-class`



(c) `Simplified` `Multi-class`



(d) `Realistic` `Multi-class`

Figure 5.20: Four evaluation strategies consisting of two player recognition approaches (`2-class` and `Multi-class`) and two contexts (`Simplified` and `Realistic`).

		Pred	
		P	**O**
GT	**P**	99.7	0.6
	O	0.3	99.4

		Pred	
		P	**O**
GT	**P**	97.5	0.8
	O	2.5	99.2

Table 5.18: `Multi-class` confusion matrices where Pred is the predicted class, GT is the ground truth class, P is the player class and O the other class. The `Simplified` context is on the left and the `Realistic` context is on the right.

	1	**2**
M	99.7	100
N	100	100

	1	**2**
M	95.0	96.7
N	97.3	98.8

Table 5.19: `2-class` subgroup accuracies where M is metronome, N is no metronome, 1 is first repeat and 2 is second repeat. The `Simplified` context is on left and the `Realistic` context is on right.

		Prediction					
		1	**2**	**3**	**4**	**5**	**6**
Ground Truth	**1**	98.8	0	0	0	0	0
	2	0	100	0	0	0	0
	3	0	0	100	0	0.6	0
	4	0	0	0	100	0.9	0
	5	1.2	0	0	0	98.5	0
	6	0	0	0	0	0	100

		Prediction						
		1	**2**	**3**	**4**	**5**	**6**	**O**
Ground Truth	**1**	96	0.8	0	1.7	0	0	0
	2	0.7	97.8	0	0	0	0	0.8
	3	0.8	0	97.9	0	0.6	0	3.4
	4	0	0	0	98.3	0	0	2.3
	5	2.5	0	2.1	0	98.8	0	0.4
	6	0	0	0	0	0	100	1.3
	O	0	1.4	0	0	0.6	0	91.8

Table 5.20: `Multi-class` confusion matrices. `Simplified` context is on left and the `Realistic` context is on right.

labelled as the other player class (0) and the dataset is divided by track into training, validation and testing respectively 75%, 12.5% and 12.5%.

5.5.3.3 Simplified Multi-class

In the third evaluation strategy, termed `Simplified Multi-class`, the aim is to be able to classify an audio segment as one of multiple players. To do this a separate class is used for each of the 6 players

(1,2,3,4,5,6) using a softmax output layer with 6 neurons (*c=6*). The `Multi-class` approach is then tested using the same evaluation methodology as the `Simplified` context used in Section 5.5.3.1.

5.5.3.4 Realistic Multi-class

In the final evaluation strategy, termed `Realistic Multi-class` the `Multi-class` approach is tested in a more realistic situation using the same two datasets and evaluation methodology from Section 5.5.3.2. However, all of audio segments from *ITM-Flute-79* are given their own new label (7).

5.5.4 Results and discussion

5.5.4.1 2-class

Figure 5.21 presents the results of each player and the mean across players for both `2-class` evaluation strategies (Figure 5.20(a) and 5.20(b)). As expected, a higher mean player accuracy is achieved in the `Simplified` context than the `Realistic` context. Player 5 achieves the lowest classification accuracy whereas player 6 achieves the highest. This could be due to player 6 having a much harder *tone* and higher harmonic energies whereas player 5 has a softer tone similar to the other four players.

A confusion matrix for the mean player results of the two `2-class` contexts are presented in table 5.18. For the `Simplified` context (Figure 5.20(a)) there is approximately the same amount of misclassified player segments as there are misclassified other player segments. In the `Realistic` context there is a substantially higher amount of misclassified player segments and the greatest decrease in performance occurs for player 1 and player 2 (Figure 5.21), because these players show less individual stylistic traits like use of ornamentation or changes in timbre.

Table 5.19 presents the `2-class` dataset category distributions of correctly classified audio segments. For both contexts, first repeat with metronome (top left) achieves the lowest accuracy and second repeat without metronome (bottom right) achieves the highest accuracy. This makes sense as an artist is generally more reserved when they are trying to stay in time with a metronome or are playing a melody for the first time.

Figure 5.21 presents the percentages of the correctly classified player segments (same as Table 5.19) for each of the tracks. Also presented are the mean accuracies for the track types (Figure 5.22). The highest accuracies are achieved on the wild tracks. This could be due to the fact that the wild tracks are chosen by the players and suit their preferred playing technique. The lowest accuracies were achieved in the Jig and Hornpipe tracks (Tracks 4, 5 and 6) and they also contain the largest decrease in accuracy between the `Simplified` and `Realistic` contexts. Reels are the most common tunes in

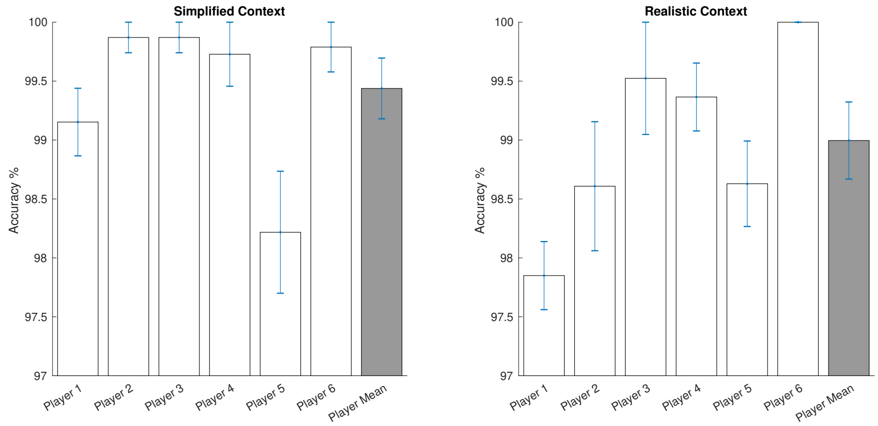


Figure 5.21: The `2-class` individual and mean player accuracies for both `Simplified` and `Realistic` contexts. Error plots display standard error across folds.

ITM. As jigs and hornpipes are less common, musicians may be less comfortable playing this type of melody.

5.5.4.2 Multi-class

Table 5.20 presents confusion matrices for the `Multi-class` evaluation strategies. Again, as expected, a higher mean accuracy is achieved in the `Simplified` context than the `Realistic` context with 99.6% and 96.6% achieved respectively. While both approaches achieve a similar accuracy in the `Simplified` context the `Multi-class` approach achieves a lower accuracy than the `2-class` approach in the `Realistic` context. In order to recognise the work of a single player, the `2-class` approach is better. As in the `2-class` evaluations, the highest overall accuracy is achieved when recognising player 6 and the lowest when recognising player 1. This is likely due to player 6 having a more individual style. The majority of the errors within the `Realistic` context are misclassified other players. Again, the few examples that are misclassified are of players with similar playing characteristics like timbre and amount of ornamentation.

In this study high accuracies are achieved suggesting that individual players can be recognised using spectral features, however the data consists of only a small number of flute players. It is expected that extending the *ITM-Flute-Style6* dataset would result in lower accuracies as new players would be similar to those represented by existing recordings.

A one-way between subjects ANOVA was conducted to compare the player recognition accuracy across all tunes and folds, including timed and untimed recordings and both first and second takes. In the `Simplified` context, there was a significant effect of the difference between recognition accuracy

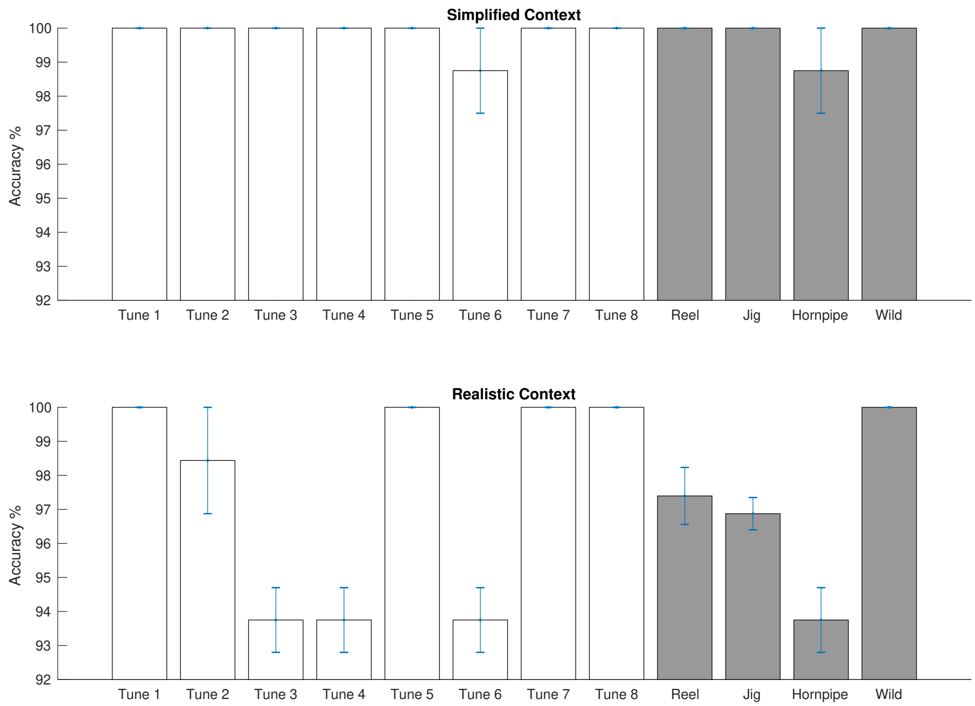


Figure 5.22: `2-class` results per track and the mean for the different track types. The `Simplified` context is above and the `Realistic` context is below. Error plots display standard error across folds.

	Player No.					
	1	2	3	4	5	6
Simplified	0.8342	**0.0275**	**0.0275**	**0.0275**	**0.0259**	**0.0275**
Realistic	0.2461	**0.0391**	**0.00002**	0.6422	**0.0316**	**0.00002**

Table 5.21: T-tests showing individual player versus all other players for `Simplified` and `Realistic` contexts. Significant results ($\rho < 0.05$) indicated in bold.

at the $\rho < 0.05$ level for the six players [F(5,354) = 4.46, $\rho = 0.0006$]. In the `Realistic` context, there was also a significant effect of the difference between recognition accuracy at the $\rho < 0.05$ level for the five players [F(5,354) = 4.41, $\rho = 0.0007$].

Results from individual player versus all other player t-tests for `Simplified` and `Realistic` contexts are shown in Table 5.21, with significant results ($\rho < 0.05$) indicated in bold.

5.5.5 Conclusions

In this study, a flute player recognition method is presented using a CNN trained on five-second solo excerpts. The method is evaluated using four strategies consisting of two approaches (`2-class` and `Multi-class`) and two contexts (`Simplified` and `Realistic`). For single player recognition, results from the evaluation show that the `2-class` method is more efficient. A player can be more easily recognised in second repeats and when not playing to a metronome. This suggests that players are less characteristic and more self-restricting when they play a tune for the first time or to a metronome. The highest accuracies are achieved when musicians play their own choice of melody (*i.e.,* wild tracks).

5.6 Chapter summary

This chapter has presented novel methods for recognition of individual traditional Irish flute players through the analysis of timbre and temporal attributes. The first study presented an analysis of timbral variations on a single note across a range of three players and six flutes using long-term average spectra and short-time magnitude values to demonstrate clear differences in harmonic magnitudes attained between individual players and smaller variations across flutes than across players.

The second study presented a technique using a Gaussian mixture method on a corpus consisting of released recordings of five players and showed identifiable timbral variations between five players across a range of notes. The study showed that the magnitudes of higher harmonics are important in identification of players at a professional level. Although the full dataset contained 99 recordings of single tunes containing a total of over 15,000 individual notes, using collected recordings resulted in little control over choice of microphone, use of audio effects or room acoustics.

In the third study, inter-onset segment classification was performed on a dataset of solo Irish flute recordings. Notes, cuts and strikes were assessed in the context of playing and different musical patterns were analysed.

The fourth study presented an onset detector using CNNs trained on solo flute data. The method used the context of each frame to detect onsets by training a range of neural networks with different amounts of prior and subsequent frames. All variants of the presented method outperformed the leading generalised method. Furthermore, training neural networks with data specific to the task is shown to be substantially more effective than training with generalised data.

The fifth study presented a technique for player recognition based on the use of convolutional neural networks trained on five-second excerpts of the playing of six players. A corpus of 168 recordings of single tunes was collected allowing for better control over content and microphone selection. The method was evaluated using two approaches, each tested in a simplified and more realistic context. Players were found to be more individually recognisable when playing the second repeat of a tune, when playing without a metronome and when playing their own choice of melody.

Chapter 6

Conclusions

6.1 Summary of thesis

The focus of this thesis has been playing style of the concert flute in Irish traditional music. After an introductory chapter (Chapter 1), this work has outlined the history and context of Irish traditional music, concentrating on the flute, the evolution of traditional music in Britain and Ireland, the history of ITM and a categorisation of the types of melodies played (Chapter 2). The design and operation of the concert flute in the context of Irish traditional music are then presented, detailing the development and evolution of the concert flute, flute acoustics and finally stylistic features and types of ornamentation (Chapter 3). A literature review of technologies used in the analysis of flute playing is then presented, encompassing the areas of timbre and onset detection (Chapter 4). A description of methods used in the identification of timbral and temporal features is presented along with five studies (Chapter 5).

A number of research questions were posed:

- *Can a corpus of recordings with relevant metadata be provided for the analysis of stylistic differences between traditional flute players?*

  At the beginning of this study, a collected corpus of solo flute tunes could not be located. Some analysis had been performed using the recordings accompanying Larsen (2003) (Kelleher et al., 2005). A corpus of recordings and metadata, known as *ITM-Flute-99*, was collected. Details of the players, tunes and sources are contained in Appendix A. The 99 recordings have a total length of approximately 1.2 hours. Ground truth metadata for event onset, pitch and class were initially created using Sonic Visualiser (Cannam et al., 2010) using the methodology described in Section 3.2.2. Sonic Visualiser was later replaced with Tony (Mauch et al., 2015) due to having more accurate pitch detection and an interface that is specifically designed for manual annotation of recordings. Manual annotation of large datasets can lead to mistakes and in this case approximately 18,000 individual events were annotated. The annotations of the *ITM-Flute-99* dataset were improved by employing a process of comparing manual and automatic onset detection followed by manual correction.

It is expected that this digital library will be a useful resource for signal analysis as well as ethnomusicology research. The dissemination of style in ITM is of interest in the field of ethnomusicology in order to determine the strength of cultural influences and regional playing styles.

A number of issues are associated with this type of corpus. There are very few instances of the same tune being recorded by multiple players and there is little information on the recording conditions of the original data. Furthermore, there is variable background information on the education and influences of the various players.

A second corpus, known as *ITM-Flute-Style6* was developed to overcome these issues. Six tunes were chosen as being common in ITM, and representing the styles of tune played by musicians in this genre. Geographical factors precluded the recording of all players in the same location but the same microphone, microphone position and interface were used. Tunes were played without and then with metronome. Furthermore, two tunes of the musician's choosing were then played. In each case, the tune was played twice in segue allowing for differences between first and second playing to be analysed. The dataset contains 128 individual recordings with a total length of approximately 2 hours. The associated background metadata is contained in Appendix C, additionally showing the results of a post-recording questionnaire.

This dataset has allowed for more detailed analysis of playing style to be undertaken and an initial study in player recognition (Ali-MacLachlan et al., 2018) has led to substantial findings, discussed in Section 5.5.

- *Can computational methods be developed that automatically identify stylistic differences between traditional flute players? Do they provide a deeper understanding of timbral and temporal components?*

In order to answer this question it is important to firstly understand the components that make up stylistic differences. Although these can be classified as timbral or temporal because they fit conveniently into the realm of signal analysis, the objective of the traditional musician is to deliver a performance in the context of that tradition where the original melody is represented in such a way as to show mastery of the medium. In this way, the musician adheres to a set of performance rules that are delivered almost unconsciously as they personalise a tune during its performance (Breathnach, 1996). A musician will change timbre and dynamics in order to present the music in a way that they would like it to be heard. They will also use ornaments to enhance the performance, introducing elements of influence from their education and context. Outwith these stylistic elements there are many, more subtle changes that can be made to a tune. Phrasing and position of breaths, alongside the amount of ornamentation can be representative of regional styles (Ó Riada, 1982). Even the choice of tune can indicate geographical locality or influential players.

Discussions concerning style in ITM are often constrained by inadequate language, leading to an unclear description and analysis of the music (Keegan, 1997; Keegan, 2011). It is therefore important to understand style from an ethnomusicological and ethnographic context, and to identify stylistic components that could be used to classify different players. Stylistic features are discussed in Section 2.5, and the work of McCullough (1977), Ó Súilleabháin (1981), Breathnach (1996) and Keegan (2010) forms a basis for the definition of these stylistic components. Additionally, regional style is discussed in Section 5.2.2, in the context of players represented in the *ITM-Flute-99* dataset (Ó Riada, 1982; Köküer et al., 2017).

The five studies discussed in Chapter 5 of this thesis encompass a range of techniques, some based on analysis of timbre and others based on temporal attributes.

Study 1 (Section 5.1) presented the findings of an exploratory study where six different flutes were played by three representative players: beginner, intermediate and expert. The analysis was limited to the note G_4, and omitted the attack and decay portions of each note. The peak magnitudes of the LTAS (see Section 4.1.2) for each of the first five harmonics were noted for each player playing each flute. The analysis of variations of the harmonic magnitudes showed that in most cases there are smaller variations across the flutes than across the players, with the overall average standard deviation being 3.7 dB across the flutes and 6.1 dB across the players. The STFT (see Section 4.1.1) of all signal frames was also presented in order to show how consistent the timbral profile of each player was when using a particular flute, and across all six flutes.

Study 2 (Section 5.2) extended this work using a larger dataset of 20 tunes (four recordings from each of five players) that were sourced from commercial recordings. In line with Study 1, analysis of a group of highly experienced players showed that they were consistently able to achieve greater magnitudes in higher order harmonics than less experienced players.

Based on the the harmonic magnitudes, an acoustic model was created for each note per player. The modelling was performed using a single multidimensional Gaussian distribution with full covariance matrix. The parameters, mean and covariance matrix of each model were estimated using the training data. Identification of players was considered from a finite set of players based on a given piece of recording from the test data, containing between one and three instances of a given note. The highest accuracy was achieved for note E_4: 57%, 63% and 68% respectively for single, two and three note instances. Note $F\#_4$ achieved the lowest accuracy, 19%, 22% and 26% which is only a little above random guess.

The accuracy in terms of player recognition was variable in this study. However results showed that professional flute players have great control over their timbre whether for consistency or in order to change timbre as part of a playing style.

The use of a corpus of released recordings in Study 2 allows for initial access to the music of a greater number of players. However, this approach has a number of shortcomings: Not all professional flute players release tracks where they are unaccompanied. There is little understanding or control as to choice of microphone, equalisation or effects although the overall track is artistically representative of the player.

Study 3 (Section 5.3) presented a note onset detection method using a feed-forward neural network trained on flute signals from the *ITM-Flute-99* corpus. Feature classes were a 13-band MFCC (excluding the first band) and 12 chroma features. The method was also appraised in comparison with ten onset detection methods that had proved successful in the MIREX woodwind instruments onset detection task. The most accurate method, `OnsetDetector` (Eyben et al., 2010), was then used.

Onset detection concentrated on notes, cuts and strikes as multi-note ornaments are constructed from these elements. When compared to ground truth onset annotations, 86%, 70% and 74% accuracies were achieved for note, cut and strike classification respectively. Using detected onsets to train the neural network as part of a fully automated system resulted in poor classification results, particularly for cuts and strikes. Analysis of the detected onsets and their context was performed, in order to establish both the degree of the errors and the musical patterns in which they occur. The results of this study showed that detection accuracy is dependant upon the context of the note, specifically the preceding and following event. In particular, strikes are difficult to detect due to the pitch deviation and overall time being small in comparison with cuts. Breaths are also difficult to detect as reverb can mask the offset at the end of the previous event.

The aim of of **Study 4** (Section 5.4) was to develop an improved onset detection system. A CNN onset detection method was presented where the network was trained solely on Irish flute recordings from the *ITM-Flute-99* dataset. A number of versions were tested, each able to analyse the onset in the context of varying amounts of preceding and following signal content. The effectiveness of this approach was evaluated by comparing two variants of the most successful version, `CNN21`, one trained with the generalised `OnsetDetector` dataset and the other trained with the flute-specific *ITM-Flute-99* dataset. These were also compared to a third method, `OnsetDetector` trained with the `OnsetDetector` dataset. The proposed `CNN21` system offered substantial improvements in accuracy and showed the advantages of training a system on specific data. Mean accuracies are: `CNN21` trained with `OnsetDetector` dataset, 66.99%; `CNN21` trained with *ITM-Flute-99* dataset, 84.62%; and `OnsetDetector` trained with `OnsetDetector` dataset, 65.44%.

This study represents a significant move towards the identification of stylistic differences through analysis of note, ornament and breath placement. As discussed in Ó Riada (1982), amount of ornamentation and length of phrasing can be indicators of regional style and would therefore be useful for determining relationships between the playing styles of different musicians.

In **Study 5** (Section 5.5) a corpus was collected by controlled recording of six players performing a set of tunes representative of those played by a typical musician in ITM. 28 recordings were made by each player (168 total). The average duration of all tracks is approximately 43 seconds. The total duration of the dataset is approximately 2 hours.

This data was used as a training set for a player recognition method using a CNN trained on approximately 1,000 five-second solo excerpts with a frequency range of 32 Hz to 4 kHz transformed into 40 MFCCs. The method is evaluated using four strategies consisting of `2-class` and `Multi-class` approaches and two contexts, `Simplified` and `Realistic`. The `2-class` approach considered a two-class problem with one player (0) against all other players (1). In the `Simplified` context only the *ITM-Flute-Style6* data was used. In the `Realistic` context, the *ITM-Flute-99* dataset was additionally incorporated in class (1). In the `Multi-class` approach, a separate class is used for each player in the `Simplified` context (1,2,3,4,5,6), and in the `Realistic` context an additional class (O) is added to represent *ITM-Flute-99*.

In the `2-class` subgroup, accuracies were between 99.7% and 100% for the `Simplified` context and between 95.0% and 98.8% for the `Realistic` context. In the `Multi-class` subgroup, accuracies were between 98.5% and 100% for the `Simplified` context and between 91.8% and 100% for the `Realistic` context. Players were more easily recognised in second repeats of tunes and when not playing to a metronome. This suggests that players are less characteristic and more self-restricting when they play a tune for the first time or to a metronome. The highest accuracies are achieved when musicians play their own choice of melody.

- *Does a discussion on the history of the flute and its operation aid the understanding of stylistic differences between players?*

  This type of study relies on an understanding of two distinct and often disparate fields of study. An understanding of the operation of the flute has been important in the development of the studies contained in this thesis. Unlike many other instruments, the flute does not always produce a distinct change in energy upon the commencement of a note. The magnitudes of various harmonics can be varied by the player in order to provide timbral variance. The style of playing in ITM is different from many other genres of music, even other types of folk music.

  Many advances in design have been made to the transverse flute (see Section 2.3) and these have been an important factor in shaping the way ITM is played on the instrument. The practical requirement for a strong sound for ensemble playing has led to the use of wide-bored instruments with large toneholes that require greater physical effort to play. Study 1 (Section 5.1) presented findings that showed the difference in harmonic magnitudes between flutes was less than between players but there are still some tonal differences between instruments (Wolfe and Smith, 2003).

- *Does an explanation of the history of Irish traditional music and how it is made on the concert flute aid the development of these computational methods?*

  Although the development of ITM has taken place over several hundred years, it is still a living tradition. Playing style has changed significantly over this time and it will be important for ethnomusicologists to capture these changes. There have been major changes from music that was predominantly played in Ireland with distinctive regional styles to music that is played internationally with a pan-Irish style (Sommers-Smith, 2001; Kearney, 2012). Flute players are influenced by the playing of other instruments as well as other flute players and there is evidence of this crossover in regional styles where the amount of ornamentation on the flute and fiddle is similar.

  In order to work alongside ethnomusicologists, it is important to have domain knowledge in order to understand the relevance of findings. Although music information retrieval (MIR) is an established field of research, much of the work has revolved around "Western" music and computer applications were not widely used in the classification of folk music (Nettl, 2010; Gómez et al., 2013). A common argument by ethnomusicologists is that human behaviour cannot be categorised but there is now an established field of research where quantitative computational analysis can exist alongside more traditional qualitative techniques (McCollum and Hebert, 2014; Tzanetakis, 2014).

The Folk Music Analysis conference[1] was started in 2011 by a group of researchers who had previously published at the International Society of Music Information Retrieval (ISMIR) conference and had expressed a desire to work in the field of computational ethnomusicology. Work contained in this thesis has been published at the Folk Music Analysis conference consistently between 2013 and 2018.

6.2 Contributions

- The development of a set of analysis methods for defining stylistic differences between Irish traditional flute players: Preliminary study with three players of differing levels showing that players contribute more towards overall timbre than individual instruments (Ali-MacLachlan et al., 2013). A method of player identification using magnitudes of partials derived from individual notes (Ali-MacLachlan et al., 2015). Development of a method for player identification using machine learning based on 5-second segments of recordings output as 40-band MFCC timbral features (Ali-MacLachlan et al., 2018).

- The *ITM-Flute-99* dataset comprising of 99 solo flute tunes played by 10 professional players. The metadata comprises over 15,000 individual notes with ground truth annotation (Köküer et al., 2014b; Köküer et al., 2017). The *ITM-Flute-Style6* dataset containing 168 recordings of 6 players . This includes all musicians playing the same melodies at the same tempo.

- A new method of producing ground truth pitch and timing metadata for solo instrumental melodies (Köküer et al., 2014b; Köküer et al., 2017). A method for error checking of manual annotation by using an onset detector and window of acceptance comparison method (Ali-MacLachlan et al., 2017).

- An appraisal of high-performing onset detection algorithms used on flute signals (Ali-MacLachlan et al., 2016). Development of training data for a machine learning algorithm that out-performs

[1] http://www.folkmusicanalysis.org/

current state-of-the-art onset detectors on solo traditional flute recordings (Ali-MacLachlan et al., 2017).

6.3 Future research

6.3.1 Analysis methods

Analysis of flute timbre has proved useful in understanding similarities between players. Evidence suggests that deep learning techniques provide more accurate results than other methods of signal analysis and in the future, work will continue on improving their performance. Other neural network architectures will be implemented in order to compare the accuracy of different methods. In order to determine whether accuracies decrease with the addition of other players, the *ITM-Flute-Style6* dataset will be extended by recording additional players.

The methods used in Study 4 show substantially higher accuracies when the system is trained on flute data in comparison to generalised data. Low accuracies were found for strikes and notes following strikes. As a strike is played by momentarily tapping a finger over a tonehole, the pitch deviation is often much smaller than that of a cut and the event time is often shorter, making it more difficult to detect.

Further development of methods used for detection of notes, cuts and strikes will allow future development of better ornament classification systems. These in turn will allow a more accurate understanding of usage of ornaments alongside phrase length and use of breaths in playing style. Understanding of this analysis would provide additional evidence as to the relationship between playing styles whether regional or otherwise.

6.3.2 Datasets

Both the *ITM-Flute-99* and *ITM-Flute-Style6* datasets have been very useful in providing a platform for initial study in this field. The data could be extended in a number of different ways.

Study 1 used a small dataset of three players who were beginner, intermediate and advanced. A larger dataset of this type would be useful in helping to identify how flute players learn. A greater understanding of the development of embouchure and timbre along with playing of ornaments and related dexterity would be very useful.

Development of the *ITM-Flute-Style6* dataset has provided interesting initial results and the possibility for further study. The ability to compare the playing of different musicians on a bar-by-bar or phrase-by-phrase basis allows for more detailed comparisons and observations. Enlarging this dataset would also be beneficial in encompassing different playing styles and to provide more training data for analysis systems.

Capturing evidence of strong regional playing styles would be very useful. Evidence suggests that these are not as prevalent and if this trend continues then it is important to collect evidence in order to aid ethnomusicology research into how playing style changes by region as well as by time.

6.3.3 Analysis of additional instruments and playing styles

The methods presented in this thesis are specific to ITM played on the concert flute but an investigation into generalising the techniques for use with other traditional instruments as well as other genres of music is planned.

In ITM, tin whistle and fiddle would be very interesting instruments to study as both are widespread in their use, and also contain soft onsets. One of the issues with fiddle is that of double stopping where two notes are played at the same time. The use of source separation or chordal analysis would be important in this case.

Analysis of Celtic playing styles would also be of great interest. There is a lot of crossover of Irish and Scottish style fiddle playing, particularly in Canada and the United States of America. Using techniques developed as part of this thesis, it may be possible to quantify the amount of influence of these national styles.

Individual player style is not purely the domain of traditional music and it is also common in Baroque music as well as other forms of European music. Analysis of players in these genres may also be of use to ethnomusicologists working in these fields of study.

6.3.4 Education

Development of computer-based tools specifically designed to aid learning of ITM may be of use to self-learners. Several potential ideas could be explored. One such area would be flute timbral training that analyses a player's tone and offers advice on strengthening harmonics based on signal analysis. Another area would be automated feedback on accuracy of playing as the transition to playing at full speed and with clear ornaments is often difficult without the help of a more experienced player. Learners often have difficulties in understanding where to deploy particular ornaments. With the analysis of existing players it may be possible in the future to develop a teaching tool that would automatically add suggested ornaments to any tune. These could be added in the context of regional styles or particular well-known players. This would allow beginners and intermediate players to learn the tunes they wanted but progress to ornaments earlier in their education and use this as a way to aid development of a personal playing style. Again, this technique is not limited by instrument or genre.

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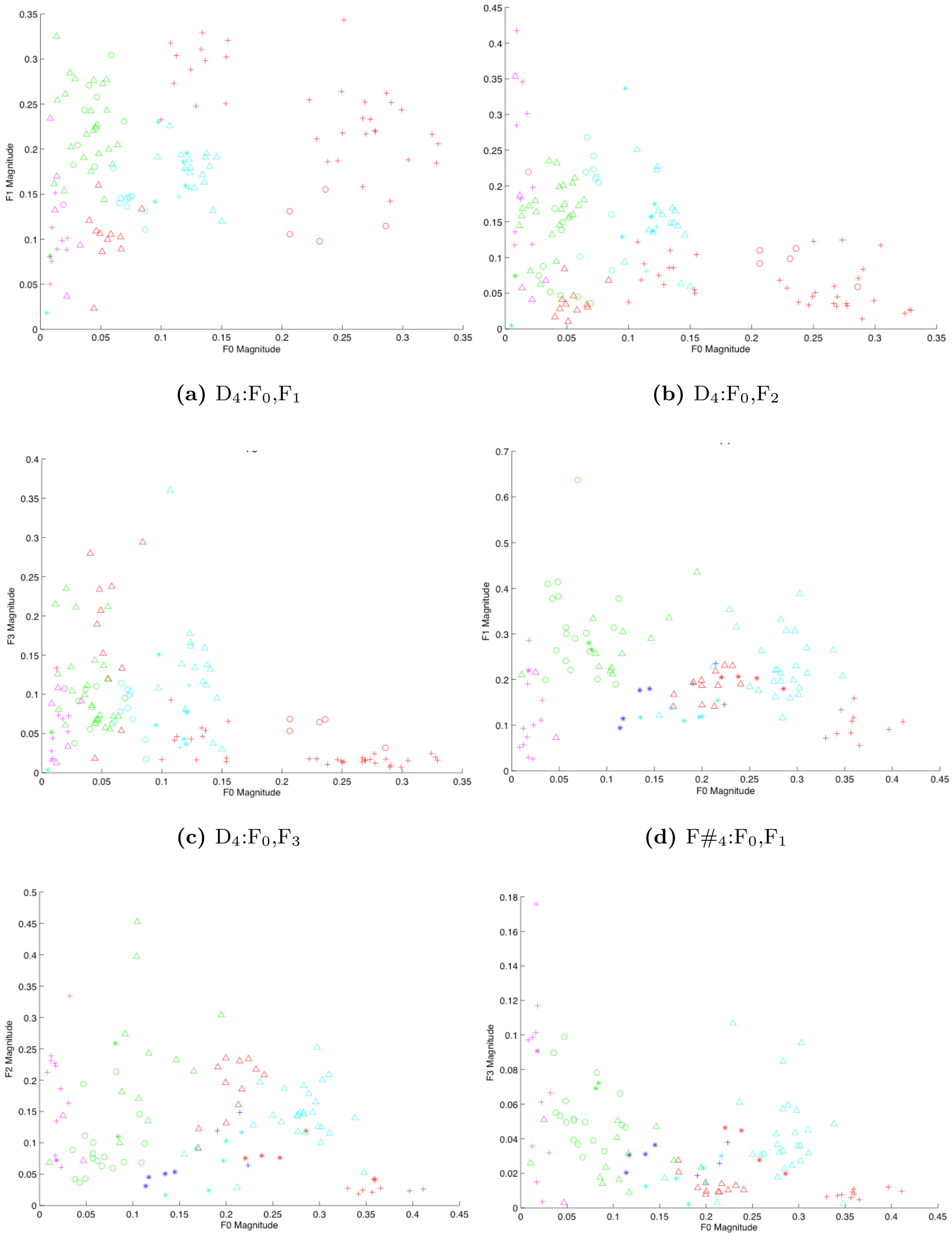
Appendices

Appendix A

Player identification, supplementary information

No.	Player	Tune	Colour	Symbol
1	Bradley, Harry	Ah Surely	blue	o
2	Bradley, Harry	The Hare's Paw	blue	*
3	Bradley, Harry	Happy To Meet Sorry To Part	blue	+
4	Bradley, Harry	The Flowers Of Red Hill	blue	^
5	Molloy, Matt	Hare In The Heather	red	o
6	Molloy, Matt	The Bush In Bloom	red	*
7	Molloy, Matt	Drowsy Maggie	red	+
8	Molloy, Matt	The Crib Of Perches	red	^
9	O'Grada, Conal	Green Mountain	green	o
10	O'Grada, Conal	The Old Copperplate	green	*
11	O'Grada, Conal	Maurice O'Keeffe's	green	+
12	O'Grada, Conal	Muing Phliuch Jig	green	^
13	Tansey, Seamus	The Flax In Bloom	magenta	o
14	Tansey, Seamus	The Maid Behind The Bar	magenta	*
15	Tansey, Seamus	Blackberry Blossom	magenta	+
16	Tansey, Seamus	Cornel Fraizer	magenta	^
17	Tubridy, Michael	For The Sake Of Old Decency	cyan	o
18	Tubridy, Michael	The Ashplant	cyan	*
19	Tubridy, Michael	The Campbells Are Coming	cyan	+
20	Tubridy, Michael	The Humours Of Derrykissanne	cyan	^

Table A.1: Players and tunes used in player identification Study 2, with marker colour and symbol in scatter graphs

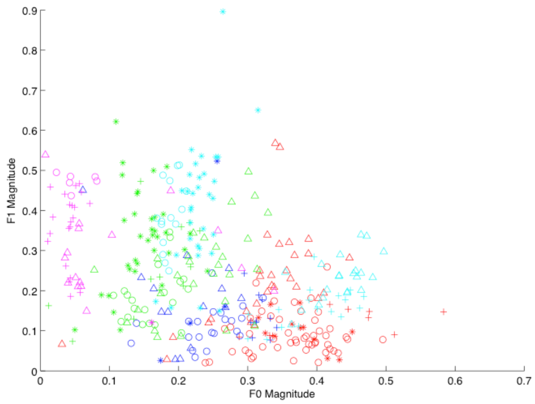


(a) D$_4$:F$_0$,F$_1$ **(b)** D$_4$:F$_0$,F$_2$

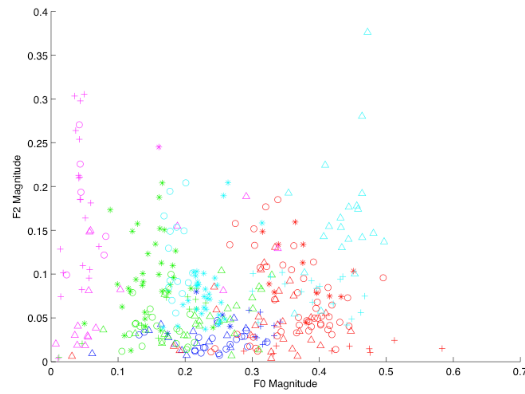
(c) D$_4$:F$_0$,F$_3$ **(d)** F#$_4$:F$_0$,F$_1$

(e) F#$_4$:F$_0$,F$_2$ **(f)** F#$_4$:F$_0$,F$_3$

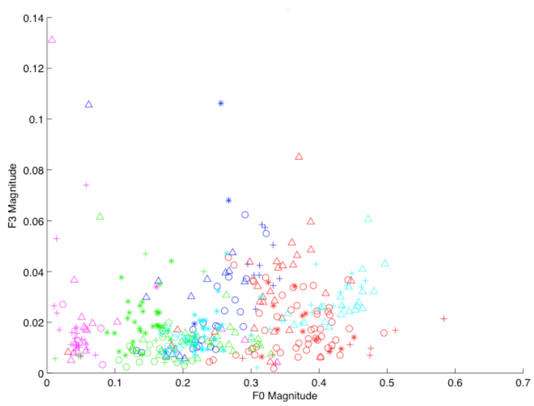
Figure A.1: Scatter plots of the short-term magnitude values at the harmonic peaks for F$_0$ against F1, F$_2$ and F3, Notes D$_4$ and F#$_4$.



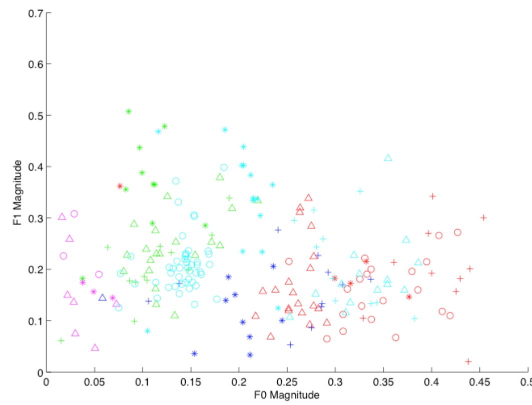
(a) A_4:F_0,F_1



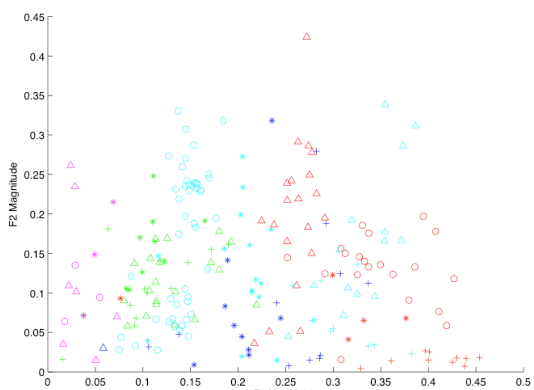
(b) A_4:F_0,F_2



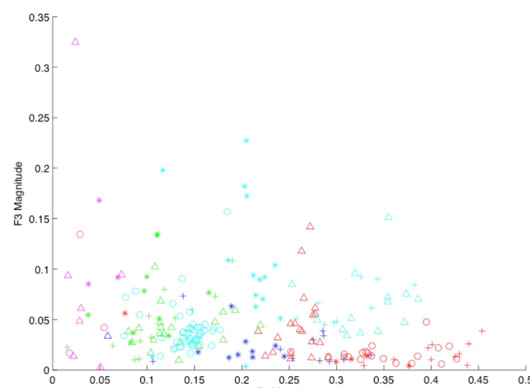
(c) A_4:F_0,F_3



(d) G_4:F_0,F_1

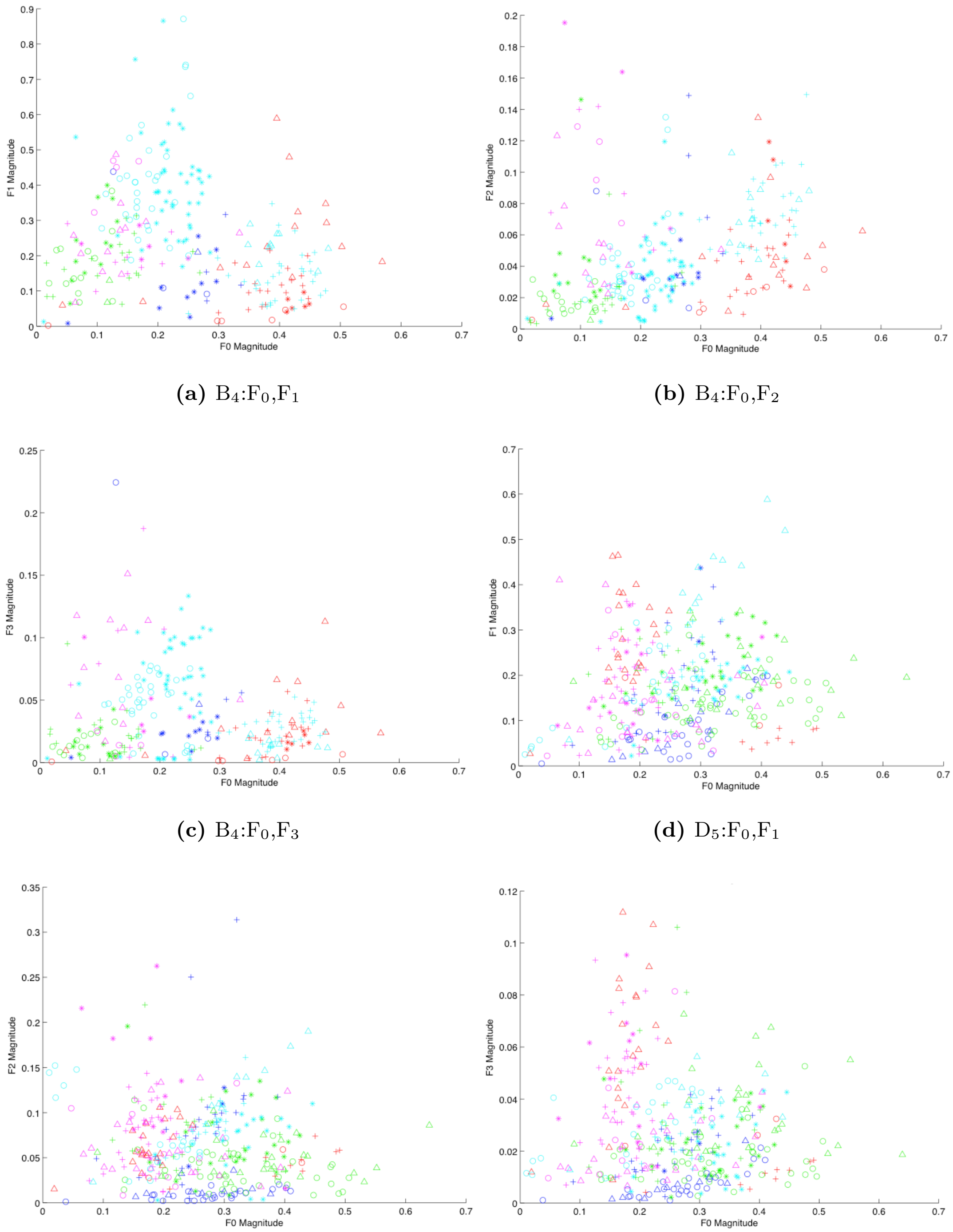


(e) G_4:F_0,F_2



(f) G_4:F_0,F_3

Figure A.2: Scatter plots of the short-term magnitude values at the harmonic peaks for F_0 against F1, F_2 and F3, Notes A_4 and G_4.

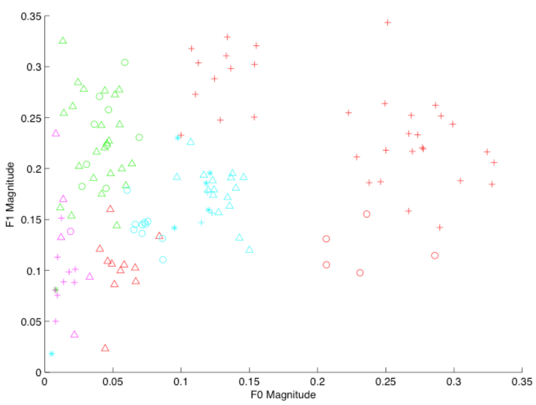


(a) B_4:F_0,F_1 **(b)** B_4:F_0,F_2

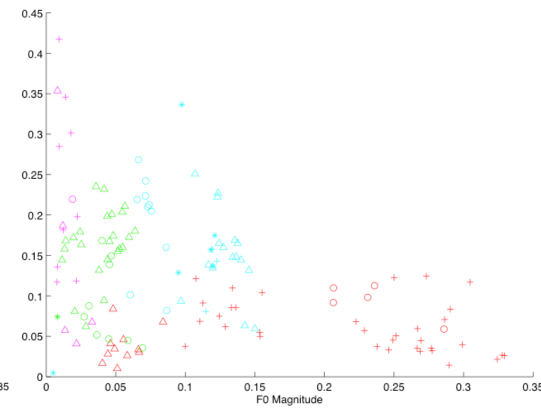
(c) B_4:F_0,F_3 **(d)** D_5:F_0,F_1

(e) D_5:F_0,F_2 **(f)** D_5:F_0,F_3

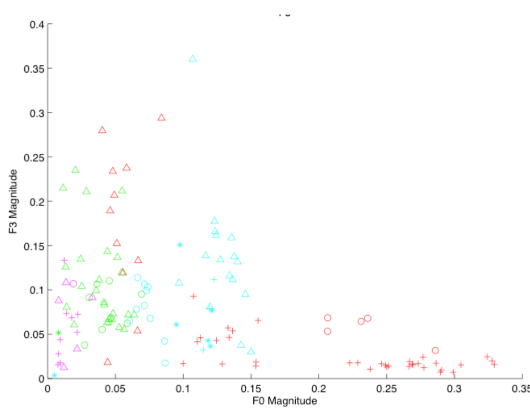
Figure A.3: Scatter plots of the short-term magnitude values at the harmonic peaks for F_0 against F1, F_2 and F3, Notes B_4 and D_5.



(a) F$\#_5$:F_0,F_1



(b) F$\#_5$:F_0,F_2



(c) F$\#_5$:F_0,F_3

Figure A.4: Scatter plots of the short-term magnitude values at the harmonic peaks for F_0 against F1, F_2 and F3, Note F$\#_5$.

Appendix B

ITM-Flute-Style6 dataset metadata

B.1 Informed consent form, ITM-Flute-Style6

Thank you for participating in our recordings. Please fill this quick survey to let us know more about you as a player.

Our goal is to gather ethnographic information related to Irish traditional music, for the development of both a contextual history in which it was made, as well as tools for the computational analysis of the music.

PRIVACY. All responses to questions that we ask may be used within the context of the current or future research studies related to the analysis/archival/preservation of Irish traditional music and associated settings (e.g., academic conferences, website for display of research findings). In addition, if you choose to participate, you will be identified in reports resulting from this study.

We know that you value your privacy, so if you wish to keep any information conveyed to the interviewer private, please make this clear in your responses. Any information declared as private will be anonymised and separated from the remainder of the interview. All data collected (including identifiable data, e.g., names and aliases) will be preserved on a secured private server, accessible only by the interviewer and the supervisor.

Participation is voluntary and you are free to withdraw from the project at any timenot just during the interview. If you wish any or all of your data to be removed from the project either during or after the interview, we will dispose of it promptly. Please note that data conveyed through the internet is subject to interception and that absolute confidentiality of any information submitted in this manner cannot be guaranteed.

SHARING. The recordings and interview data may be made available to others for the purposes of academic enquiry. In this case recordings and question responses will be anonymised.

PARTICIPANT'S STATEMENT: "I am 18 years of age or older, I have read the description of the research project and by completing this questionnaire, I hereby agree to participate. I am aware that the content of this interview will be used for research purposes, and that I may withdraw at any time, if I so wish".

This research is conducted by Islah Ali-MacLachlan (PhD student) under the supervision of Birmingham City University Lecturer Dr.Jason Hockman, Contact islah.ali-maclachlan@bcu.ac.uk or jason.hockman@bcu.ac.uk for more information.

DMT Lab, Department of Digital Media Technology Birmingham City University, Millennium Point, Curzon Street, Birmingham B4 7XG Telephone 0121 331 5400

B.1.1 Player 1

Figure B.1: Rudall & Rose c1821 8-key flute with Chris Wilkes head

What do you like/dislike about your flute. Please describe the tone of the flute as well as other physical attributes.

The best thing about the old Rudall is its full tone, overtones and versatility, although much of that is due to the magic of the Chris Wilkes head and embouchure cut.

How many years experience do you have playing the flute?

7-9

What other instruments do you play? How long have you played them for?

I've played music since the age of five and gone through various different wind instruments and musical genres, starting with descant recorder, clarinet, saxophone, whistle, simple flute.

Who or what influenced you to play traditional music?

Although I was aware of traditional music, and some friends who played trad tunes, I was late coming to it as a main focus for my own playing, in my early 40s. That was mainly due to spending more time in Ireland through change in work and family connections. But the existence of web based resources also helped a lot (such as Chiff&Fipple and Whistle This!). I was helped a lot by generous advice from whistle/piper Peter Laban from Miltown at the beginning.

Who are your favourite flute players? What do you particularly like about their playing?

Although I've paid some attention to McKenna and the classic north Connaught styles, I've always found it a bit harsh and been interested in strong melodic players and in set dance music. Catherine McEvoy was an inspiration in combining a Sligo/Roscommon rhythmic style with great musicality and articulation. However, I shifted my focus more towards the music of East Galway and North Munster. So I spent time listening to Mike Rafferty and other Ballinakil players (notably Eddie Moloney, Tommy Whelan, Jack Coen, Paddy Carty). Des Mulkere shared ideas about phrasing in the 'old style'. PJ Crotty from the Tulla band, Paddy Taylor and Louise Mulcahy from Limerick. But I would also be influenced by playing with C#/D accordion players like Charlie Harris and Andrew MacNamara.

Have you made a conscious effort to sound more like your favourite flute players? If so,

What has influenced your playing style?						
1 = Highly influential, 5 = Not influential						
	1	2	3	4	5	n/a
Instrument teacher		x				
Recordings	x					
Attending concerts			x			
Tutorial videos				x		
Books, printed material		x				
Playing in sessions		x				
Festival Workshops		x				

Table B.1: Player 1, What has influenced your playing style?

how did you do this?

Mainly by combining some elements. Some phrasing and breathing from Mike Rafferty. Using more slide/taps in addition cuts, from Louise Mulcahy. Thinking about ways to emphasise bottom D from Conal O'Grada.

Do you play flute in a regional style? Please describe the style and how you came to play it.

I don't think so, but I would say not in the more common North Connaught style and I would assiciate more with an East Clare and South Galway style and repertoire (Tulla and Shaskeen bands etc).

What other styles of music do you play?

Whistle, uilleann pipes. I also play guitar (pop, jazz, funk etc) and have played jazz sax in the past.

How important have the following learning methods been in developing your flute playing technique?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Private teacher					x	
Group Lessons			x			
Comhaltas		x				
Festival workshops		x				
Sessions	x					
Learning from friends/family			x			
Self-learn online videos		x				
Self-learn DVDs, VHS, etc				x		
Self-learn books			x			

Table B.2: Player 1, How important have the following learning methods been in developing your flute playing technique?

How important are the following elements in your overall playing style?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Cuts and strikes	x					
Rolls and cranns		x				
Timbre/tone		x				
Speed		x				
Dynamics			x			
Swing	x					
Variation				x		
Emphasis	x					
Intonation		x				
Repertoire		x				

Table B.3: Player 1, How important are the following elements in your overall playing style?

What techniques do you find important when learning new tunes?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Reading sheet music	x					
Learn from recording	x					
Learn from video content		x				
Learn to sing it			x			
Play with others		x				

Table B.4: Player 1, What techniques do you find important when learning new tunes?

B.1.2 Player 2

Figure B.2: Rudall & Rose 8-key flute with Chris Wilkes head

What do you like/dislike about your flute. Please describe the tone of the flute as well as other physical attributes.

It makes pretty much the sound I have in my mind's ear of my ideal for this class of flute, when my playing is good enough to be able to coax it out. I have different ideals for other classes of flute..... I like the dark tone of a good R&R style flute, the "dark chocolate" smoothness with lots of low partials in the fundamental tone. Like most antiques it has intonation "issues". I have played better flutes........ For me it is essential to have all the 8 keys and that they be in working order - I use them.

How many years experience do you have playing the flute?

20+

What other instruments do you play? How long have you played them for?

Whistle (as long as flute, 40+ years), pibgorn (c10 years) bodhran (c15 years)

Who or what influenced you to play traditional music?

Friends met at University, transfer from other musical and wider interests (classical, especially baroque on period instruments), David Munrow's Pied Piper radio series and his LPs, general background (including exposure to folk song at primary school with the BBC Singing Together series), interest in folklore generally and also interest in old artefacts, especially old flutes.......

Who are your favourite flute players? What do you particularly like about their playing?

Trad: Jean-Michel Veillon, Matt Molloy, Harry Bradley, Calum Stewart.

Period Instrument: Stephen Preston, Barthold Kuijken, Lisa Beznosiuk, Jed Wentz, Anna Besson.

Have you made a conscious effort to sound more like your favourite flute players? If so, how did you do this?

Only loosely/generally, in trying to get a more finger-articulated and flowing style and a richer, reedier, “honkier” tone.

Do you play flute in a regional style? Please describe the style and how you came to play it.

What has influenced your playing style?						
1 = Highly influential, 5 = Not influential						
	1	2	3	4	5	n/a
Instrument teacher					x	
Recordings			x			
Attending concerts			x			
Tutorial videos						x
Books, printed material			x			
Playing in sessions		x				
Festival Workshops			x			

Table B.5: Player 2, What has influenced your playing style?

No.

What other styles of music do you play? I am not classically trained nor at all competent, but I try to play Baroque music on my 8-key Romantic flute from time to time and always have done.

How important have the following learning methods been in developing your flute playing technique?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Private teacher					x	
Group Lessons					x	
Comhaltas						x
Festival workshops				x		
Sessions		x				
Learning from friends/family			x			
Self-learn online videos						x
Self-learn DVDs, VHS, etc						x
Self-learn books					x	

Table B.6: Player 2, How important have the following learning methods been in developing your flute playing technique?

How important are the following elements in your overall playing style?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Cuts and strikes	x					
Rolls and cranns	x					
Timbre/tone	x					
Speed			x			
Dynamics				x		
Swing		x				
Variation		x				
Emphasis	x					
Intonation		x				
Repertoire			x			

Table B.7: Player 2, How important are the following elements in your overall playing style?

What techniques do you find important when learning new tunes?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Reading sheet music		x				
Learn from recording		x				
Learn from video content			x			
Learn to sing it			x			
Play with others		x				

Table B.8: Player 2, What techniques do you find important when learning new tunes?

B.1.3 Player 3

Figure B.3: Michael Grinter large holed Rudall model with 8 keys

What do you like/dislike about your flute. Please describe the tone of the flute as well as other physical attributes.

It has a strong, clear tone, with massive dynamic capabilities. Wide tonal range, dark and full in the lower octave and sweet in the higher octaves. Powerful tone without being too loud. The embrochure can be a little challenging, and it doesn't like to behave very much if it's too warm/humid, but it's a cracking flute.

How many years experience do you have playing the flute?

4-6

What other instruments do you play? How long have you played them for?

Guitar, piano, drums, bouzouki, whistle. 15+ years

Who or what influenced you to play traditional music?

Family, culture and heritage/tradition

Who are your favourite flute players? What do you particularly like about their playing?

Dave Sheridan, has some of the most dynamic and impressive flute playing around. Louise Mulcahy, has exceptionally strong tone and powerful aggressive style.

Do you play flute in a regional style? Please describe the style and how you came to play it.

I don't think I intentionally play with any regional style. I try and emulate flute techniques that I like from other flute players, and draw on other instruments (fiddle and box) for my phrasing. I guess it'd be closest to a Roscommon style, probably medium to hard blown.

What other styles of music do you play? see above for other instruments. Styles include blues, folk, acoustic, rock.

What has influenced your playing style?						
1 = Highly influential, 5 = Not influential						
	1	2	3	4	5	n/a
Instrument teacher						x
Recordings	x					
Attending concerts		x				
Tutorial videos						x
Books, printed material					x	
Playing in sessions	x					
Festival Workshops					x	

Table B.9: Player 3, What has influenced your playing style?

How important have the following learning methods been in developing your flute playing technique?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Private teacher						x
Group Lessons						x
Comhaltas						x
Festival workshops					x	
Sessions	x					
Learning from friends/family		x				
Self-learn online videos						x
Self-learn DVDs, VHS, etc						x
Self-learn books						x

Table B.10: Player 3, How important have the following learning methods been in developing your flute playing technique?

How important are the following elements in your overall playing style?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Cuts and strikes	x					
Rolls and cranns	x					
Timbre/tone	x					
Speed		x				
Dynamics	x					
Swing	x					
Variation	x					
Emphasis	x					
Intonation	x					
Repertoire		x				

Table B.11: Player 3, How important are the following elements in your overall playing style?

What techniques do you find important when learning new tunes?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Reading sheet music			x			
Learn from recording		x				
Learn from video content					x	
Learn to sing it	x					
Play with others		x				

Table B.12: Player 3, What techniques do you find important when learning new tunes?

B.1.4 Player 4

Make and model of your flute.

Figure B.4: Eamonn Cotter 6 keyed Blackwood flute

What do you like/dislike about your flute. Please describe the tone of the flute as well as other physical attributes.

Like: Lots of happy memories together with my flute! I love the feel of the wood and the way I can feel the air vibrate through the wood in my fingers I think it's a beautiful looking instrument It is is a very expressive instrument capable of a great range of tone and dynamics Its the best flute I have ever played

Dislikes: Perhaps a temperamental instrument and even after playing it for I dont know how many years I am still learning how to get the best out of the instrument and discovering new things about myself and the instrument

How many years experience do you have playing the flute?

20+

What other instruments do you play? How long have you played them for?

Tin Whistle occasionally

Who or what influenced you to play traditional music?

I was sent to tin whistle lessons as a child and participated in Fleadh and score competitions

Who are your favourite flute players? What do you particularly like about their playing?

Friends

My friend Joe is a lovely flute player. Also my friend Maria Murphy. Love the sound of her playing. In both cases, I feel their flute style reflects their personalities. In other words, I like those people and I like the sound of their playing as it reminds me of them

Darragh Fadden - beautiful strong tone and creative variations

They all play in tune!

Famous players

Marcus O Murchu - Beautiful expressive strong tone and thoughtful style

What has influenced your playing style?						
1 = Highly influential, 5 = Not influential						
	1	2	3	4	5	n/a
Instrument teacher	x					
Recordings			x			
Attending concerts			x			
Tutorial videos						x
Books, printed material						x
Playing in sessions		x				
Festival Workshops		x				

Table B.13: Player 4, What has influenced your playing style?

Catherine McEvoy - Incredible, unique tone

Kevin Henry - Lovely breathy tone and unusual settings of tunes

Tansey - A genius who has taken flute playing to the highest level. Incredibly creative and passionate musician

Jean Michelle Vellion - Wonderful technical ability to play expressively in 3 octaves. Also his repertoire. Listening to his playing makes me cry sometimes its so beautiful

Have you made a conscious effort to sound more like your favourite flute players? If so, how did you do this?

No, but Ive learned tunes from them, so I have picked up a bit of their styles that way

Do you play flute in a regional style? Please describe the style and how you came to play it.

I don't think so :-)

What other styles of music do you play?

None

How important have the following learning methods been in developing your flute playing technique?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Private teacher					x	
Group Lessons					x	
Comhaltas					x	
Festival workshops			x			
Sessions		x				
Learning from friends/family			x			
Self-learn online videos					x	
Self-learn DVDs, VHS, etc					x	
Self-learn books					x	

Table B.14: Player 4, How important have the following learning methods been in developing your flute playing technique?

How important are the following elements in your overall playing style?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Cuts and strikes		x				
Rolls and cranns		x				
Timbre/tone	x					
Speed	x					
Dynamics	x					
Swing	x					
Variation	x					
Emphasis	x					
Intonation	x					
Repertoire		x				

Table B.15: Player 4, How important are the following elements in your overall playing style?

What techniques do you find important when learning new tunes?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Reading sheet music					x	
Learn from recording	x					
Learn from video content		x				
Learn to sing it					x	
Play with others		x				

Table B.16: Player 4, What techniques do you find important when learning new tunes?

B.1.5 Player 5

Make and model of your flute.

Figure B.5: Bernard Lee 8-key, made between 1838-1840 in Old Bond Street, London

What do you like/dislike about your flute. Please describe the tone of the flute as well as other physical attributes.

Please describe the tone of the flute as well as other physical attributes.

I love the rich tone of the flute and the volume, and feel it fits my hand-size perfectly (I have quite small hands and the flute is made using what appear to be Rudall and Rose dimensions - with the small finger holes - from that era). The only thing I dislike is the slightly problematic intonation (which is a flaw of old pre-A=440 flutes generally) although having played it for many years I have learned to work with it.

How many years experience do you have playing the flute?

20+

What other instruments do you play? How long have you played them for? Tin whistle - approx 40 years; metal (Boehm) flute: approx 40 years; concertina - approx 40 years; recorder - approx 47 years; fiddle - on and off thirty years, but only more seriously the last three months

Who or what influenced you to play traditional music? Family members were my biggest primary influence (specifically older brother Kevin, who plays fiddle, and former brother-in-law Mike - also a fiddle player). Also, as a teenager, I was very impressed by and encouraged by established musicians in the local area (Tom Walsh - piper from Preston, Dave Lyth, fiddler from Lancaster). Big early influence: hearing recorded Irish trad music at a young age and becoming obsessed with it (formative influences: the Chieftains, Boys of the Lough, De Dannan, Bothy Band etc etc). From early 20s onwards: Michael Feely - flute and fiddle player from Lancashire, but with roots in Leitrim (who I was married to for a while). Michael was a big aficionado of Sligo-style and we played together as a flute duo for many years. This undoubtedly influenced the path my music took (and is still taking).

Who are your favourite flute players? What do you particularly like about their playing?

What has influenced your playing style?						
1 = Highly influential, 5 = Not influential						
	1	2	3	4	5	n/a
Instrument teacher					x	
Recordings		x				
Attending concerts					x	
Tutorial videos						x
Books, printed material						x
Playing in sessions	x					
Festival Workshops						x

Table B.17: Player 5, What has influenced your playing style?

Flute players I have met and played with: Harry McGowan from Carrowmore in S. Sligo is my top favourite. Also other flute players I have spent time playing with in/from S. Sligo and Connaught region generally - Joe Stenson, Peter Horan, Packie Duignan, Roger Sherlock. In terms of flute players I like on recordings (but have not played with to any great degree): Catherine McEvoy, Harry Bradley. My favourite flute style is that found in Sligo/Leitrim/Roscommon. I like the strong rhythm and tone, and the use of strategically-placed breath spaces as a feature to further accentuate the rhythm. I love the repertoire of these players.

Have you made a conscious effort to sound more like your favourite flute players? If so, how did you do this?

To a certain degree, by learning the same settings of tunes, although a lot of my effort has been unconscious and a result of playing with/listening to the players I like a lot. I have tended to pick up the style in a fairly natural way mostly by listening. I once also attended a master-class by Mary Bergin (mid-1980s), who gave me invaluable pointers about use of ornamentation. Whilst not a Sligo player per se (She is from Dublin), Mary's approach to ornamentation is applicable to Sligo style and has helped shape my playing ever since.

Do you play flute in a regional style? Please describe the style and how you came to play it.

I describe myself as a Sligo style player, as I spent a lot of time in S. Sligo/Leitrim playing with local musicians, and adopted that style as my own. It is my favourite style of flute playing. In the

How important have the following learning methods been in developing your flute playing technique?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Private teacher						x
Group Lessons					x	
Comhaltas					x	
Festival workshops					x	
Sessions	x					
Learning from friends/family	x					
Self-learn online videos						x
Self-learn DVDs, VHS, etc						x
Self-learn books						x

Table B.18: Player 5, How important have the following learning methods been in developing your flute playing technique?

mid-1980s I was close friends with a family who were neighbours of Harry McGowan in Carrowmore, near Tubbercurry, and spent a lot of time in that area. I have recordings made of Harry playing tunes in his kitchen and learned a lot about the local style from listening to Harry and playing with him, and also with another local flute player, Joe Stenson (a lovely, encouraging man who I always enjoy playing with). I also spent a lot of time playing with Peter Horan, who had a more 'choppy' John McKenna-type approach, but still had the same feel as Harry's slightly more 'modern' (!) approach - ie a strong emphasis on the beat and bouncing off lower notes. I have learned a big chunk of the local repertoire by playing in sessions there.

What other styles of music do you play? I play folk music more generally, playing along on songs etc with various bands. On the metal flute I play a small amount of blues, plus some contemporary flute 'classics' like the flute solo in California Dreamin'. I also play Dave Brubeck's 'Take Five', which I have adapted to create a 6/8 jig version!

How important are the following elements in your overall playing style?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Cuts and strikes	x					
Rolls and cranns	x					
Timbre/tone	x					
Speed	x					
Dynamics	x					
Swing	x					
Variation	x					
Emphasis	x					
Intonation	x					
Repertoire	x					

Table B.19: Player 5, How important are the following elements in your overall playing style?

What techniques do you find important when learning new tunes?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Reading sheet music					x	
Learn from recording	x					
Learn from video content	x					
Learn to sing it					x	
Play with others	x					

Table B.20: Player 5, What techniques do you find important when learning new tunes?

B.1.6 Player 6

Make and model of your flute.

Figure B.6: George Ormiston Rudall & Rose Model 6 keys.

What do you like/dislike about your flute. Please describe the tone of the flute as well as other physical attributes.

I love the tone... I'd like to lengthen the C natural key.

How many years experience do you have playing the flute?

20+

What other instruments do you play? How long have you played them for?

Tin Whistle for 43 years

Who or what influenced you to play traditional music? My mum. She is a lover of music but couldn't play. A big part of my identity as Manchester Irish growing up.

Who are your favourite flute players? What do you particularly like about their playing?

Roger Sherlock. Tone, tempo, tastful use of ornaments. Roger Sherlock: Tone. Kevin Henry: rhythm, drive, tempo. Marian Egan (Teacher: Ornamentation, breath control).

Have you made a conscious effort to sound more like your favourite flute players? If so, how did you do this?

By osmosis... listening and listening. Playing along to records.

Do you play flute in a regional style? Please describe the style and how you came to play it.

I play Sligo style. My teacher was from Sligo... although to say there is a specific Sligo style is debatable...

What other styles of music do you play?

Asturian folk

What has influenced your playing style?						
1 = Highly influential, 5 = Not influential						
	1	2	3	4	5	n/a
Instrument teacher	x				x	
Recordings	x				x	
Attending concerts	x				x	
Tutorial videos						x
Books, printed material					x	
Playing in sessions	x					
Festival Workshops						x

Table B.21: Player 6, What has influenced your playing style?

How important have the following learning methods been in developing your flute playing technique?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Private teacher						x
Group Lessons	x					
Comhaltas	x					
Festival workshops			x			
Sessions	x					
Learning from friends/family	x					
Self-learn online videos						x
Self-learn DVDs, VHS, etc						x
Self-learn books						x

Table B.22: Player 6, How important have the following learning methods been in developing your flute playing technique?

How important are the following elements in your overall playing style?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Cuts and strikes	x					
Rolls and cranns	x					
Timbre/tone	x					
Speed	x					
Dynamics	x					
Swing	x					
Variation			x			
Emphasis	x					
Intonation		x				
Repertoire	x					

Table B.23: Player 6, How important are the following elements in your overall playing style?

What techniques do you find important when learning new tunes?						
1 = Very important, 5 = Not important						
	1	2	3	4	5	n/a
Reading sheet music			x			
Learn from recording	x					
Learn from video content			x			
Learn to sing it			x			
Play with others	x					

Table B.24: Player 6, What techniques do you find important when learning new tunes?