

Chapter 5

Sense in Expressive Music Performance: Data Acquisition, Computational Studies, and Models

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About this Chapter

This chapter gives an introduction to basic directions of current research in expressive music performance. A special focus is given on the various methods to acquire performance data either during a performance (e.g. through computer-monitored instruments) or from audio recordings. We then sur-

vey computational approaches to formalise and model the various aspects in expressive music performance. Future challenges and open problems are discussed briefly at the end of the chapter.

5.1 Introduction

Millions of people are regularly attending live music events or listening to recordings of music performances. What drives them to do so is hard to pin down with certainty, and the reasons for it might be manifold. But while enjoying the music, they are all listening to (mostly) human-made music that contains a specific human expression, whatever kind it might be – what they hear makes intuitive sense to them. Without this expressivity the music would not attract people; it is an integral part of the music.

Given the central importance of expressivity (not only in music, but in all communication modes and interaction contexts), it is not surprising that human expression and expressive behaviour have become a domain of intense scientific study. In the domain of music, much research has focused on the act of *expressive music performance*, as it is commonly and most typically found in classical music: the deliberate shaping of the music by the performer, the imposing of expressive qualities onto an otherwise “dead” musical score via controlled variation of parameters such as intensity, tempo, timing, articulation, etc. Early attempts at quantifying this phenomenon date back to the beginning of the 20th century, and even earlier than that.

If we wish to precisely measure and analyse every detail of an expressive music performance (onset timing, timbre and intensity, duration, etc.), we end up with huge amounts of data that quickly become unmanageable. Since the first large-scale, systematic investigations into expression in music performance (usually of classical music) in the 1930s, this has always been a main problem, which was controlled either by reducing the amount of music investigated to some seconds of music, or by limiting the number of performances studied to one or two. Recent approaches try to overcome this problem by using modern computational methods in order to study, model, and understand

musical performance in its full complexity.

In the past ten years, some very comprehensive overview papers have been published on the various aspects of music performance research. The probably most cited is Alf Gabrielsson's chapter in Diana Deutsch's book "Psychology of Music" (Gabrielsson, 1999), in which he reviewed over 600 papers in this field published until approximately 1995. In a follow-up paper, he added and discussed another 200 peer-reviewed contributions that appeared until 2002 (Gabrielsson, 2003). A cognitive-psychological review has been contributed by Palmer (1997) summarising empirical research that focuses on cognitive aspects of music performance such as memory retrieval, anticipatory planning, or motor control. The musicologist's perspective is represented by two major edited books devoted exclusively to music performance research (Rink, 1995, 2002). Lately, more introductory chapters highlight the various methodological issues of systematic musicological performance research (Rink, 2003; Clarke, 2004; Cook, 2004; Windsor, 2004). Two recent contributions surveyed the diversity of computational approaches to modelling expressive music performance (De Poli, 2004; Widmer and Goebel, 2004). Parncutt and McPherson (2002) attempted to bridge the gap between research on music performance and music practice by bringing together two authors from each of the two sides for each chapter of their book.

Considering this variety of overview papers, we aim in this chapter to give a systematic overview on the more technological side of accessing, measuring, analysing, studying, and modelling expressive music performances. As a start, we survey the current literature of the past century on various ways of obtaining expression-related data from music performances. Then, we review current computational models of expressive music performance. In a final section we briefly sketch possible future directions and open problems that might be tackled by future research in this field.

5.2 Data acquisition and preparation

This section is devoted to very practical issues of obtaining precise empirical data on expressive performance. We can distinguish basically two different strategies for obtaining information on music performance. The first is to monitor performances during the production process with various measurement devices (MIDI pianos, accelerometers, movement sensors, video systems, etc.). Specific performance parameters can be accessed directly (hammer velocity of each played tone, bow speed, fingering, etc.). The other way is to extract all these relevant data from the recorded audio signal. This method has the disadvantage that some information, easy to extract during performance, is almost impossible to gain from the audio domain (consider, for instance, the sustain pedal on the piano). The advantage, however, is that we now have more than a century of recorded music at our disposal that could serve as a valuable resource for various kinds of scientific investigation. In the following sub-sections, we discuss the various approaches for monitoring and measuring music performance, and survey the major empirical performance studies that used them. As will be seen, by far the largest part of research has been done on piano performances.

5.2.1 Using specially equipped instruments

Before computers and digital measurement devices were invented and readily available for everyone, researchers employed a vast variety of mechanical and electrical measurement apparati to capture all sorts of human or mechanical movements during performance. We will review the most important of them, in chronological order, from rather old to state-of-the-art.

Mechanical and electro-mechanical setups

Among the first to record the movement of piano keys were Binet and Courtier (1895), who used a 6-mm caoutchouc rubber tube placed under the keys that was connected to a cylindric graphical recorder that captured continuous air

pressure resulting from striking different keys on the piano. They investigated some basic pianistic tasks such as playing trills, connecting tones, or passing-under of the thumb in scales with exemplary material. In the first of the two contributions of this study, Ebhardt (1898) mounted metal springs on a bar above the strings that closed an electrical shutter when the hammer was about to touch the strings. The electric signal was recorded with a kymograph and timed with a 100-Hz oscillator. He studied the timing precision of simple finger tapping and playing scales. Further tasks with binary and ternary metrum revealed some characteristic timing patterns (e.g. a lengthening of the time interval before an accentuated onset). Onset and offset timing of church hymn performances were investigated by Sears (1902). He equipped a reed organ with mercury contacts that registered key depression of 10 selected keys. This information was recorded on four tracks on the surface of a smoked kymograph drum. He studied several temporal aspects of performances by four organ players, such as duration of the excerpts, bars, and individual note values, accent behavior, or note overlap (articulation).

A multitude of mechanical measurement devices were introduced by Ortmann (1925, 1929) in studies on physiological determinants of piano playing. To investigate the different behaviors of the key, he mounted a tuning fork to the side of one piano key that wrote wave traces into smoked paper which varied with the speed of the key. With this setup, he was one of the first to study the response of the key in different pianistic playing techniques. For assessing finger movements, Ortmann (1929, p. 230) used a custom-built mechanical apparatus with non-flexible aluminum strips that, on one side, were connected to either the finger (proximal phalanx) or the key surface and, on the other side, wrote onto a revolving drum. With this apparatus, continuous displacement of finger and key could be recorded and analysed. Another mechanical system was the “Pantograph” (Ortmann, 1929, p. 164), a parallelogram lever construction to record lateral arm movement. For other types of movement, he used active optical systems. The motion of a tiny light bulb attached to the wrist or the finger left a trace on a photo plate (the room was kept in very subdued light) when the shutter of the photo camera remained open for the entire duration of the movement.

Similar active markers mounted on head, shoulder, elbow, and wrist were used by Bernstein and Popova in their important study in 1930 (reported by Kay et al., 2003) to study the complex interaction and coupling of the limbs in piano playing. They used their “kymocyclographic camera” to record the movements of the active markers. A rotating shutter allowed the light of the markers to impinge on the constantly moving photographic film. With this device they could record up to 600 instances of the movement per second.

Piano rolls as a data source

A special source of expression data are piano rolls for reproducing pianos by different manufacturers (e.g. Welte-Mignon, Hupfeld, Aeolian Duo-Art, Ampico). A number of renowned pianists made recordings on these devices in the early part of the 20th century (Bowers, 1972; Hagmann, 1984). Such pianos were the first means to record and store artistic music performances before the gramophone was invented. Starting in the late 1920s, scientists took advantage of this source of data and investigated various aspects of performance. Heinlein (1929a,b, 1930) used Duo-Art rolls by the Aeolian company to study pedal use of four pianists playing Schumann’s *Träumerei*. Rolls of the same company were the basis of Vernon’s 1936 study. He investigated vertical synchronisation of the tones in a chord (see Goebel, 2001). Hartmann (1932) used Hupfeld “Animatic Rolls” and provided a very detailed study on tone and bar durations as well as note onset asynchronies in two recordings (by Josef Pembaur and Harold Bauer) of the first movement of Beethoven’s “Moonlight Sonata” Op. 27 No. 2. Since the precise recording procedures used by these companies are still unknown (they were deliberately held back for commercial reasons), the authenticity of these rolls is sometimes questionable (Hagmann, 1984; Gottschewski, 1996). For example, the Welte-Mignon system was able to simultaneously control dynamics only for keyboard halves. Hence, emphasising the melody note and playing the rest of the chord tones more softly was only possible when the melody tone was played at a different point in time than the others (Gottschewski, 1996, pp. 26–42). Although we know today that pianists anticipate melody notes (Palmer, 1996b; Repp, 1996c; Goebel, 2001), the Welte-Mignon rolls cannot be taken literally as a source for

studying note asynchronies (as done by Vernon, 1936). The interpretation of piano rolls must be done with care, keeping in mind the conditions of their production. There are currently some private attempts to systematically scan piano rolls and transform them into standard symbolic format (e.g. MIDI). However, we are not aware of any scientific project concerned with this.

The Iowa piano camera

During the 1930s, Carl E. Seashore guided a research group that focused on different aspects of music performance, namely the singing voice, violin playing, and piano performance (Seashore, 1932, 1936b,a). They developed various measurement setups for scientific investigation, among them the “Iowa Piano Camera” (Henderson et al., 1936) that optically captured onset and offset times and hammer velocity of each key and additionally the movement of the two pedals. It was therefore a complete and rather precise device that was not topped until the advent of modern computer-controlled pianos (such as the Disklavier or the Bösendorfer SE, see Goebel and Bresin, 2003). Each hammer is equipped with a shutter that controls light exposure of a moving film. The hammer shutter interrupts the light exposure on the film twice: a first time from 24 to 12 mm before the hammer touches the strings, and a second time at hammer–string contact. The average hammer speed of the last 12 mm of the hammer’s travel can be inferred from the distance on the film between these two interrupts (today’s computer-controlled pianos take the average speed of the final 5 mm). According to Skinner and Seashore (1936), the temporal resolution is around 10 ms. The hammer velocity is quantised into 17 dynamics categories (Henderson, 1936). With this system, the IOWA group performed several studies with professional pianists. Henderson (1936) had two professionals play the middle section of Chopin’s Nocturne Op. 15 No. 3. In this very comprehensive study, they examined temporal behavior, phrasing, accentuation, pedalling, and chord asynchronies. Skinner and Seashore (1936) analysed repeated performances of pieces by Beethoven and Chopin and found high timing consistency among the pianists.

Henry Shaffer's photocell Bechstein

After the efforts of Seashore's research group at Iowa, it took over 40 years before a new group of researchers used modern technology to capture piano performance. It was L. Henry Shaffer at Exeter who equipped each of the 88 keys of a Bechstein grand piano with pairs of photocells to capture the essential expressive parameters of piano performance (Shaffer, 1980, 1981, 1984; Shaffer et al., 1985; Shaffer and Todd, 1987; Shaffer, 1992). The optical registration of the action's movements had the advantage of not affecting the playability of the piano. The photocells were mounted in the piano action in pairs, each capturing the moment of the hammer's transit. One was placed to register the instant of hammer-string contact, the other one the resting position of the hammer. The position of the two pedals were monitored by micro switches and stored as 12-bit words on the computer. Each such event was assigned a time stamp rounded to the nearest microsecond. The sensor at the strings yielded the note onset time, the one at the hammer's resting position (when the hammer returns) the note offset time. The time difference between the two sensors was an inverse estimate of the force at which the key was depressed. This technology is in principle identical to the computer-monitored pianos that are commercially available now (e.g. the Yamaha Disklavier series or the Bösendorfer SE).

Studies with synthesiser keyboards or digital pianos

Before computer-monitored acoustic pianos became widely available, simple synthesiser keyboards or digital pianos were used to capture expressive data from music performances. These devices provide timing and loudness data for each performed event through the standardised digital communications protocol MIDI (Musical Instrument Digital Interface) (Huber, 1999). However, such keyboards do not provide a realistic performance setting for advanced pianists, because the response of the keys is very different from an acoustic piano and the synthesised sound (especially with extensive use of the right pedal) does not satisfy the trained ears of highly skilled pianists.

Still, such electronic devices were used for various general expression

studies (e.g. Palmer, 1989, 1992; Repp, 1994a,b, 1995c; Desain and Honing, 1994). Bruno Repp later repeated two of his studies that were first performed with data from a digital piano (Repp, 1995c, concerned with legato articulation; Repp, 1996b, concerned with the use of the right pedal) on a computer-controlled grand piano (Repp, 1997c,b, respectively). Interestingly, the results of both pairs of studies were similar to each other, even though the acoustic properties of the digital piano were considerably different from the grand piano.

The Yamaha Disklavier system

Present performance studies dealing with piano performances generally make use of commercially available computer-controlled acoustic pianos. Apart from systems that can be built into a piano (e.g. Autoklav, Pianocorder, see Coenen and Schäfer, 1992), the most common is the Disklavier system by Yamaha. The first computer-controlled grand pianos were available from 1989 onwards. The Mark IV series that is currently available includes also a computer with screen and several high-level functions such as an automatic accompaniment system. From 1998, Yamaha introduced their high-end PRO series of Disklaviers that involves an extended MIDI format to store more than 7-bit velocity information (values from 0 to 127) and information on key release.

There were few attempts to assess the Disklavier's accuracy in recording and reproducing performances. Coenen and Schäfer (1992) compared various reproducing systems (among them a Disklavier DG2RE and a SE225) with respect to their usability for reproducing compositions for mechanical instruments. More systematic tests on recording and reproduction accuracy were performed by Goebel and Bresin (2001, 2003) using accelerometer registration to inspect key and hammer movements during recording and reproduction.

Yamaha delivers both upright and grand piano versions of its Disklavier system. The upright model was used for several performance studies (Palmer and van de Sande, 1993; Palmer and Holleran, 1994; Repp, 1995a,b, 1996c,a,d, 1997d,a). The Yamaha Disklavier grand piano was even more widely used.

Moore (1992) combined data from a Disklavier grand piano with electromyographic recordings of the muscular activity of four performers playing trills. Behne and Wetekam (1994) recorded student performances of the theme from Mozart's K.331 sonata on a Disklavier grand piano and studied systematic timing variations of the Siciliano rhythm. As mentioned above, Repp repeated his work on legato and pedalling on a Disklavier grand piano (Repp, 1997c,b). Juslin and Madison (1999) used a Disklavier grand piano to record and play back different (manipulated) performances of two melodies to assess listeners' ability to recognise simple emotional categories. Bresin and Battel (2000) analysed multiple performances recorded on a Disklavier grand piano of Mozart's K.545 sonata in terms of articulation strategies. Clarke and Windsor (2000) used recordings made on a Disklavier grand piano for perceptual evaluation of real and artificially created performances. A short piece by Beethoven was recorded on a Disklavier grand piano played by one (Windsor et al., 2001) and by 16 professional pianists (Timmers et al., 2002; Timmers, 2002) in different tempi. Timing characteristics of different types of grace notes were investigated. Riley-Butler (2002) used a Disklavier grand piano in educational settings. She presented students with piano roll representations of their performances and observed considerable increase of learning efficiency with this method.

Bösendorfer's SE system

The SE ("Stahnke Electronics") System dates back to the early 1980s when the engineer Wayne Stahnke developed a reproducing system in cooperation with the MIT Artificial Intelligence Laboratory. It was built into a Bösendorfer Imperial grand piano (Roads, 1986; Moog and Rhea, 1990). A first prototype was ready in 1985; the system was officially sold by Kimball (at that time owner of Bösendorfer) starting from summer 1986. This system was very expensive and only few academic institutions could afford it. Until the end of its production, only about three dozen of these systems have been built and sold. In principle, the SE works like the Disklavier system (optical sensors register hammershank speed and key release, and linear motors reproduce final hammer velocity). However, its recording and reproducing capabilities

are superior even compared with other much younger systems (Goebel and Bresin, 2003). Despite its rare occurrence in academic institutions, it was used for performance research in some cases.

Palmer and Brown (1991) performed basic tests on the relationship between hammer velocity and peak amplitude of the resulting sound. Repp (1993) tried to estimate peak sound level of piano tones from the two lowest partials as measured in the spectrogram and compared a digital piano, a Disklavier MX100A upright piano, with the Bösendorfer SE. Studies in music performance were performed at Ohio State University (Palmer and van de Sande, 1995; Palmer, 1996b,a), at the Musikhochschule Karlsruhe (e.g. Mazzola and Beran, 1998; Mazzola, 2002, p. 833), and on the grand piano located at the Bösendorfer company in Vienna (Goebel, 2001; Widmer, 2001, 2002b, 2003; Goebel and Bresin, 2003; Widmer, 2005).

Very recently (2006), the Bösendorfer company in Vienna has finished development of a new computer-controlled reproducing piano called “CEUS” that includes, among other features, sensors that register the continuous motion of each key. These data might be extremely valuable for studies regarding pianists’ touch and tone control.

5.2.2 Measuring audio by hand

An alternative to measuring music expression during performance through sensors placed in or around the performer or the instrument is to analyse the recorded sound of music performances. This has the essential advantage that any type of recording may serve as a basis for investigation, e.g. commercially available CDs, historic recordings, or recordings from ethnomusicological research. One could just simply go into a record store and buy all the performances by the great pianists of the past century.¹

However, extracting precise performance information from audio is difficult and sometimes impossible. The straight-forward method is to inspect

¹In analysing recordings the researcher has to be aware that almost all records are glued together from several takes so the analysed performance might never have taken place in this particular rendition (see also Clarke, 2004, p. 88).

the waveform of the audio signal with computer software and mark manually with a cursor the onset times of selected musical events. Though this method is time-consuming, it delivers timing information with a reasonable precision. Dynamics is a more difficult issue. Overall dynamics (loudness) can be measured (e.g. by reading peak energy values from the root-mean-square of the signal averaged over a certain time window), but we are not aware of a successful procedure to extract individual dynamics of simultaneous tones (for an attempt, see Repp, 1993). Many other signal processing problems have not been solved either (e.g. extracting pedal information, tone length and articulation, etc., see also McAdams et al., 2004).

First studies that extracted timing information directly from sound used oscillogram filming (e.g. Bengtsson and Gabrielsson, 1977; for more references see Gabrielsson, 1999, p. 533). Povel (1977) analysed gramophone records of three performances of Johann Sebastian Bach's first prelude of *The Well-Tempered Clavier*, Vol. I. He determined the note onsets "by eye" from two differently obtained oscillograms of the recordings (which were transferred onto analog tape). He reported a temporal precision of 1–2 ms (!). Recordings of the same piece were investigated by Cook (1987), who obtained timing (and intensity) data with a computational method. Onset detection was automated by a threshold procedure applied to the digitised sound signal (8 bit, 4 kHz) and post-corrected by hand. He reported a timing resolution of 10 ms. He also stored intensity values, but did not specify in more detail what exactly was measured there.

Gabrielsson et al. (1983) analysed timing patterns of performances from 28 different monophonic melodies played by 5 performers. The timing data were measured from the audio recordings with a precision of ± 5 ms (p. 196). In a later study, Gabrielsson (1987) extracted both timing and (overall) intensity data from the theme of Mozart's sonata K.331. In this study, a digital sampling system was used that allowed a temporal precision of 1–10 ms. The dynamics was estimated by reading peak amplitudes of each score event (in voltages). Nakamura (1987) used a Brüel & Kjær level recorder to register dynamics of solo performances played on a violin, oboe, and recorder. He analysed the produced dynamics in relation to the perceived intensity of the music.

The first larger corpus of recordings was measured by Repp (1990) who fed 19 recordings of the third movement of Beethoven's piano sonata Op. 31 No. 3 into a VAX 11/780 computer and read off the note onsets from waveform displays. In cases of doubt, he played the sound up to the onset and moved the cursor stepwise back in time, until the following note was no longer audible (Repp, 1990, p. 625). He measured the performances at the quarter-note level² and reported an absolute mean error of 6.5 ms for repeated measurements (equivalent to 1% of the inter-onset intervals, p. 626). In a further study, Repp (1992) collected 28 recordings of Schumann's "Träumerei" by 24 renowned pianists. He used a standard waveform editing program to hand-measure the 10-kHz sampled audio files. The rest of the procedure was identical (aural control of ambiguous onsets). He reported an average absolute measurement error of 4.3 ms (or less than 1%). In his later troika on the "microcosm of musical expression" (Repp, 1998, 1999a,b), he applied the same measurement procedure on 115 performances of the first five bars of Chopin's Etude Op. 10 No. 3 collected from libraries and record stores. He also extracted overall intensity information (Repp, 1999a) by taking the peak sound levels (pSPL in dB) extracted from the root-mean-square (RMS) integrated sound signal (over a rectangular window of 30 ms).

Nettheim (2001) measured parts of recordings of four historical performances of Chopin's e-minor Nocturne Op. 72 No. 1 (Pachmann, Godowsky, Rubinstein, Horowitz). He used a time-stretching software to reduce the playback speed by a factor of 7 (without changing the pitch of the music). He then simply took the onset times from a time display during playback. Tone onsets of all individual tones were measured with this method.³ In repeated measurements, he reported an accuracy of around 14 ms. In addition to note onset timing, he assigned arbitrary intensity values to each tone ranging from 1 to 100 by ear.

In recent contributions on timing and synchronisation in jazz performances, the timing of the various instruments of jazz ensembles was inves-

²In the second part of this paper, he measured and analysed eight-note and sixteenth-note values as well.

³Obviously, the chosen excerpts were slow pieces with a comparatively low note density.

tigated. Friberg and Sundström (2002) measured cymbal onsets from spectrogram displays with a reported precision of ± 3 ms. Ashley (2002) studied the synchronisation of the melody instruments with the double bass line. He repeatedly measured onsets of both lines from waveform plots of the digitised signal with usual differences between the measurements of 3–5 ms. About the same level of consistency (typically 2 ms) was achieved by Collier and Collier (2002) through a similar measurement procedure (manual annotation of physical onsets in trumpet solos). Lisboa et al. (2005) used a wave editor to extract onset timing in solo cello performances; Moelants (2004) made use of a speech transcription software (“Praat”) to assess trill and ornament timing in solo string performances.

In a recent commercial enterprise, John Q. Walker and colleagues have been trying to extract the complete performance information out of historical (audio) recordings in order to play them back on a modern Disklavier.⁴ Their commercial aim is to re-sell old recordings with modern sound quality or live performance feel. They computationally extract as much performance information as possible and add the missing information (e.g. tone length, pedalling) to an artificially-created MIDI file. They use it to control a modern Disklavier grand piano and compare this performance to the original recording. Then they modify the added information in the MIDI files and play it back again and repeat this process iteratively until the Disklavier’s reproduction sounds “identical” to the original recording (see also Midgette, 2005).

Another way of assessing temporal content of recordings is by tapping along with the music recording e.g. on a MIDI drum pad or a keyboard, and recording this information (Cook, 1995; Bowen, 1996; Bachmann, 1999). This is a comparably fast method to gain rough timing data at a tappable beat level. However, perceptual studies on tapping along with expressive music showed that tappers – even after repeatedly tapping along with the same short piece of music – still underestimate abrupt tempo changes or systematic variations (Dixon et al., 2005).

⁴<http://www.zenph.com>

5.2.3 Computational extraction of expression from audio

The most general approach to extracting performance-related data directly from audio recordings would be fully automatic transcription, but such systems are currently not robust enough to provide the level of precision required for analysis of expression (Klapuri, 2004). However, more specialised systems were developed with the specific goal of expression extraction, in an attempt to support the painstaking effort of manual annotation (e.g. Dixon, 2000). Since the score is often available for the performances being analysed, Scheirer (1997) recognised that much better performance could be obtained by incorporating score information into the audio analysis algorithms, but his system was never developed to be sufficiently general or robust to be used in practice. One thing that was lacking from music analysis software was an interface for interactive editing of partially correct automatic annotations, without which the use of the software was not significantly more efficient than manual annotation.

The first system with such an interface was BeatRoot (Dixon, 2001a,b), an automatic beat tracking system with a graphical user interface which visualised (and auralised) the audio and derived beat times, allowing the user to edit the output and retrack the audio data based on the corrections. BeatRoot produces a list of beat times, from which tempo curves and other representations can be computed. Although it has its drawbacks, this system has been used extensively in studies of musical expression (Goebel and Dixon, 2001; Dixon et al., 2002; Widmer, 2002a; Widmer et al., 2003; Goebel et al., 2004). Recently, Gouyon et al. (2004) implemented a subset of BeatRoot as a plug-in for the audio editor WaveSurfer (Sjölander and Beskow, 2000).

A similar methodology was applied in the development of JTranscriber (Dixon, 2004), which was written as a front end for an existing transcription system (Dixon, 2000). The graphical interface shows a spectrogram scaled to a semitone frequency scale, with the transcribed notes superimposed over the spectrogram in piano roll notation. The automatically generated output can be edited with simple mouse-based operations, with audio playback of the original and the transcription, together or separately.

These tools provide a better approach than manual annotation, but

since they have no access to score information, they still require a significant amount of interactive correction, so that they are not suitable for very large scale studies. An alternative approach is to use existing knowledge, such as from previous annotations of other performances of the same piece of music, and to transfer the metadata after aligning the audio files. The audio alignment system MATCH (Dixon and Widmer, 2005) finds optimal alignments between pairs of recordings, and is then able to transfer annotations from one recording to the corresponding time points in the second. This proves to be a much more efficient method of annotating multiple performances of the same piece, since manual annotation needs to be performed only once. Further, audio alignment algorithms are generally much more accurate than techniques for direct extraction of expressive information from audio data, so the amount of subsequent correction for each matched file is much less.

Taking this idea one step further, the initial annotation phase can be avoided entirely if the musical score is available in a symbolic format, by synthesising a mechanical performance from the score and matching the audio recordings to the synthetic performance. For analysis of expression in audio, e.g. tempo measurements, the performance data must be matched to the score, so that the relationship between actual and nominal durations can be computed. Several score-performance alignment systems have been developed for various types of music (Cano et al., 1999; Soulez et al., 2003; Turetsky and Ellis, 2003; Shalev-Shwartz et al., 2004).

Other relevant work is the on-line version of the MATCH algorithm, which can be used for tracking live performances with high accuracy (Dixon, 2005a,b). This system is being developed for real time visualisation of performance expression. The technical issues are similar to those faced by score-following systems, such as those used for automatic accompaniment (Dannenberg, 1984; Orio and Déchelle, 2001; Raphael, 2004), although the goals are somewhat different. Matching involving purely symbolic data has also been explored. Cambouropoulos developed a system for extracting score files from expressive performances in MIDI format (Cambouropoulos, 2000). After manual correction, the matched MIDI and score files were used in detailed studies of musical expression. Various other approaches to symbolic score-

performance matching are reviewed by Heijink et al. (2000b,a).

5.2.4 Extracting expression from performers' movements

While the previous sections dealt with the extraction of expression contained in music performances, this section is devoted to expression as represented in all kinds of movements that occur when performers interact with their instruments during performance (for an overview, see Davidson and Correia, 2002; Clarke, 2004). Performers' movements are a powerful communication channel of expression to the audience, sometimes even overriding the acoustic information (Behne, 1990; Davidson, 1994).

There are several ways to monitor performers' movements. One possibility is to connect mechanical devices to the playing apparatus of the performer (Ortmann, 1929), but that has the disadvantage of inhibiting the free execution of the movements. More common are optical tracking systems that either simply video-tape a performer's movements or record special passive or active markers placed on particular joints of the performer's body. We already mentioned an early study by Bernstein and Poppova (1930), who introduced an active photographic tracking system (Kay et al., 2003). Such systems use light-emitting markers placed on the various limbs and body parts of the performer. They are recorded by video cameras and tracked by software that extracts the position of the markers (e.g. the Selspot System, as used by Dahl, 2004, 2005). The disadvantage of these systems is that the participants need to be cabled, which is a time-consuming process. Also, the cables might inhibit the participants to move as they would normally move. Passive systems use reflective markers that are illuminated by external lamps. In order to create a three-dimensional picture of movement, the data from several cameras are coupled by software (Palmer and Dalla Bella, 2004).

Even less intrusive are video systems that simply record performance movements without any particular marking of the performer's limbs. Elaborated software systems (e.g. EyesWeb⁵, see Camurri et al., 2004, 2005) are able to track defined body joints directly from the plain video signal (see Camurri

⁵<http://www.megaproject.org>

and Volpe, 2004, for an overview on gesture-related research). Perception studies on communication of expression through performers' gestures use simpler point-light video recordings (reflective markers on body joints recorded in a darkened room) to present them to participants for ratings (Davidson, 1993).

5.2.5 Extraction of emotional content from MIDI and audio

For listeners and musicians, an important aspect of music is its ability to express emotions (Juslin and Laukka, 2004). An important research question has been to investigate the coupling between emotional expression and the underlying musical parameters. Two important distinctions have to be made. The first distinction is between perceived emotional expression ("what is communicated") and induced emotion ("what you feel"). Here, we will concentrate on the perceived emotion which has been the focus of most of the research in the past. The second distinction is between compositional parameters (pitch, melody, harmony, rhythm) and performance parameters (tempo, phrasing, articulation, accents). The influence of compositional parameters has been investigated for a long time starting with the important work of Hevner (1937). A comprehensive summary is given in Gabrielsson and Lindström (2001). The influence of performance parameters has recently been investigated in a number of studies (for overviews see Juslin and Sloboda, 2001; Juslin, 2003). These studies indicate that for basic emotions such as happy, sad or angry, there is a simple and consistent relationship between the emotional description and the parameter values. For example, a sad expression is generally characterised by slow tempo, low sound level, legato articulation, and a happy expression is often characterised by fast tempo, moderate sound level and staccato articulation.

Predicting the emotional expression is usually done in a two-step process (Lindström et al., 2005). The first step extracts the basic parameters from the incoming signal. The selection of parameters is a trade-off between what is needed in terms of emotion-mapping and what is possible. MIDI performances are the simplest case in which the basic information in terms of notes, dynamics and articulation is already available. From this data it is possible

to deduce for example the tempo using beat-tracking methods as described above. Audio from monophonic music performances can also be analyzed at the note level, which gives similar parameters as in the MIDI case (with some errors). In addition, using audio, a few extra parameters are available such as the spectral content and the attack velocity. The CUEX algorithm by Friberg et al. (2005) was specifically designed for prediction of emotional expression; it determines eight different parameters for each recognised note. Polyphonic audio is the most difficult case which has only recently been considered. One possibility is to first perform note extraction using polyphonic transcription (e.g. Klapuri, 2004) and then extract the parameters. Due to the lack of precision of polyphonic transcription there will be many errors. However, this may not be too problematic for the prediction of the emotion if the mapping is redundant and insensitive to small errors in the parameters. A more straightforward approach is to extract overall parameters directly from audio, such as using auditory-based measures for pitch, rhythm and timbre (Leman et al., 2004; Liu et al., 2003).

The second step is the mapping from the extracted parameters to the emotion character. A typical data-driven method is to use listener ratings (the “right” answer) for a set of performances to train a model. Common statistical/mathematical models are used such as regression (Leman et al., 2004; Juslin, 2000), Bayesian networks (Canazza et al., 2003), or Hidden Markov Models (Dillon, 2003).

5.3 Computational models of music performance

As the preceding sections have demonstrated, a large amount of empirical data about expressive performance has been gathered and analysed (mostly using statistical methods). The ultimate goal of this research is to arrive at an understanding of the relationships between the various factors involved in performance that can be formulated in a general model. Models describe relations among different kinds of observable (and often measurable) information about a phenomenon, discarding details that are felt to be irrelevant. They serve to generalise empirical findings and have both a descriptive and predic-

tive value. Often the information is quantitative and we can distinguish input data, supposedly known, and output data, which are inferred by the model. In this case, inputs can be considered as the causes, and outputs the effects of the phenomenon. Computational models – models that are implemented on a computer – can compute the values of output data corresponding to the provided values of inputs. This process is called simulation and is widely used to predict the behaviour of the phenomenon in different circumstances. This can be used to validate the model, by comparing the predicted results with actual observations.

5.3.1 Modelling strategies

We can distinguish several strategies for developing the structure of the model and finding its parameters. The most prevalent ones are analysis-by-measurement and analysis-by-synthesis. Recently also methods from artificial intelligence have been employed: machine learning and case based reasoning. One can distinguish local models, which operate at the note level and try to explain the observed facts in a local context, and global models that take into account the higher level of the musical structure or more abstract expression patterns. The two approaches often require different modelling strategies and structures. In certain cases, it is possible to devise a combination of both approaches. The composed models are built by several components, each one aiming to explain different sources of expression. However, a good combination of the different parts is still quite a challenging research problem.

Analysis by measurement

The first strategy, analysis-by-measurement, is based on the analysis of deviations from the musical notation measured in recorded human performances. The goal is to recognise regularities in the deviation patterns and to describe them by means of a mathematical model, relating score to expressive values (see Gabrielsson 1999 and Gabrielsson 2003, for an overview of the main results). The method starts by selecting the performances to be analyzed. Often

rather small sets of carefully selected performances are used. The physical properties of every note are measured using the methods seen in section 5.2 and the data so obtained are checked for reliability and consistency. The most relevant variables are selected and analysed. The analysis assumes an interpretation model that can be confirmed or modified by the results of the measurements. Often the assumption is made that patterns deriving from different sources or hierarchical levels can be separated and then added. This assumption helps the modelling phase, but may be overly simplistic. The whole repertoire of statistical data analysis techniques is then available to fit descriptive or predictive models onto the empirical data – from regression analysis to linear vector space theory to neural networks or fuzzy logic.

Many models address very specific aspects of expressive performance, for example, the final ritard and its relation to human motion (Kronman and Sundberg, 1987; Todd, 1995; Friberg and Sundberg, 1999; Sundberg, 2000; Friberg et al., 2000b); the timing of grace notes (Timmers et al., 2002); vibrato (Desain and Honing, 1996; Schoonderwaldt and Friberg, 2001); melody lead (Goebel, 2001, 2003); legato (Bresin and Battel, 2000); or staccato and its relation to local musical context (Bresin and Widmer, 2000; Bresin, 2001).

A global approach was pursued by Todd in his phrasing model (Todd, 1992, 1995). This model assumes that the structure of a musical piece can be decomposed into a hierarchy of meaningful segments (phrases), where each phrase is in turn composed of a sequence of sub-phrases. The fundamental assumption of the model is that performers emphasise the hierarchical structure by an *accelerando-ritardando* pattern and a *crescendo-decrescendo* pattern for each phrase, and that these patterns are superimposed (summed) onto each other to give the actually observed complex performance. It has recently been shown empirically on a substantial corpus of Mozart performances (Tobudic and Widmer, 2006) that this model may be appropriate to explain (in part, at least) the shaping of dynamics by a performer, but less so as a model of expressive timing and tempo.

Analysis by synthesis

While analysis by measurement develops models that best fit quantitative data, the analysis-by-synthesis paradigm takes into account the human perception and subjective factors. First, the analysis of real performances and the intuition of expert musicians suggest hypotheses that are formalised as rules. The rules are tested by producing synthetic performances of many pieces and then evaluated by listeners. As a result the hypotheses are refined, accepted or rejected. This method avoids the difficult problem of objective comparison of performances, including subjective and perceptual elements in the development loop. On the other hand, it depends very much on the personal competence and taste of a few experts.

The most important model developed in this way is the KTH rule system (Friberg, 1991, 1995; Friberg et al., 1998, 2000a; Sundberg et al., 1983, 1989, 1991). In the KTH system, a set of rules describe quantitatively the deviations to be applied to a musical score, in order to produce a more attractive and human-like performance than the mechanical one that results from a literal playing of the score. Every rule tries to predict (and to explain with musical or psychoacoustic principles) some deviations that a human performer is likely to apply. Many rules are based on a low-level structural analysis of the musical score. The KTH rules can be grouped according to the purposes that they apparently have in music communication. For instance, differentiation rules appear to facilitate categorisation of pitch and duration, whereas grouping rules appear to facilitate grouping of notes, both at micro and macro levels.

Machine learning

In the “traditional” way of developing models, the researcher normally makes some hypothesis on the performance aspects s/he wishes to model and then tries to establish the empirical validity of the model by testing it on real data or on synthetic performances. An alternative approach, pursued by Widmer and coworkers (Widmer, 1995a,b, 1996, 2000, 2002b; Widmer and Tobudic, 2003; Widmer, 2003; Widmer et al., 2003; Widmer, 2005; Tobudic and Widmer, 2006), tries to extract new and potentially interesting regularities and performance

principles from many performance examples, by using machine learning and data mining algorithms (see also Chapter 4 in this book). The aim of these methods is to search for and discover complex dependencies on very large data sets, without a specific preliminary hypothesis. A possible advantage is that machine learning algorithms may discover new (and possibly interesting) knowledge, avoiding any musical expectation or assumption. Moreover, some algorithms induce models in the form of rules that are directly intelligible and can be analysed and discussed with musicologists. This was demonstrated in a large-scale experiment (Widmer, 2002b), where a machine learning system analysed a large corpus of performance data (recordings of 13 complete Mozart piano sonatas by a concert pianist), and autonomously discovered a concise set of predictive rules for note-level timing, dynamics, and articulation. Some of these rules turned out to describe regularities similar to those incorporated in the KTH performance rule set (see above), but a few discovered rules actually contradicted some common hypotheses and thus pointed to potential shortcomings of existing theories.

The note-level model represented by these learned rules was later combined with a machine learning system that learned to expressively shape timing and dynamics at various higher levels of the phrase hierarchy (in a similar way as described in Todd's 1989; 1992 structure-level models), to yield a multi-level model of expressive phrasing and articulation (Widmer and Tobudic, 2003). A computer performance of a (part of a) Mozart piano sonata generated by this model was submitted to the International Performance Rendering Contest (RENCON) in Tokyo, 2002, where it won the Second Prize behind a rule-based rendering system that had been carefully tuned by hand. The rating was done by a jury of human listeners. This can be taken as a piece of evidence of the musical adequacy of the model. However, as an explanatory model, this system has a serious shortcoming: in contrast to the note-level rules, the phrase-level performance model is not interpretable, as it is based on a kind of case-based learning (see also below). More research into learning structured, interpretable models from empirical data will be required.

Case-based reasoning

An alternative approach, closer to the observation-imitation-experimentation process observed in humans, is that of directly using the knowledge implicit in human performances. Case-based reasoning (CBR) is based on the idea of solving new problems by using (often with some kind of adaptation) similar previously solved problems. An example in this direction is the SaxEx system for expressive performance of jazz ballads (Arcos et al., 1998; López de Mántaras and Arcos, 2002), which predicts expressive transformations to recordings of saxophone phrases by looking at how other, similar phrases were played by a human musician. The success of this approach greatly depends on the availability of a large amount of well-distributed previously solved problems, which are not easy to collect.

Mathematical theory approach

A rather different model, based mainly on mathematical considerations, is the Mazzola model (Mazzola, 1990; Mazzola and Zahorka, 1994; Mazzola et al., 1995; Mazzola, 2002; Mazzola and Göller, 2002). This model basically consists of a musical structure analysis part and a performance part. The analysis part involves computer-aided analysis tools, for various aspects of the music structure, that assign particular weights to each note in a symbolic score. The performance part, that transforms structural features into an artificial performance, is theoretically anchored in the so-called Stemma Theory and Operator Theory (a sort of additive rule-based structure-to-performance mapping). It iteratively modifies the performance vector fields, each of which controls a single expressive parameter of a synthesised performance.

The Mazzola model has found a number of followers who studied and used the model to generate artificial performances of various pieces. Unfortunately, there has been little interaction or critical exchange between this “school” and other parts of the performance research community, so that the relation between this model and other performance theories, and also the empirical validity of the model, are still rather unclear.

5.3.2 Perspectives

Computer-based modelling of expressive performance has shown its promise over the past years and has established itself as an accepted methodology. However, there are still numerous open questions related both to the technology, and to the questions that could be studied with it. Two prototypical ones are briefly discussed here.

Comparing performances and models

A problem that naturally arises in quantitative performance research is how performances can be compared. In subjective comparison often a supposed “ideal” performance is used as a reference by the evaluator. In other cases, an actual reference performance can be assumed. Of course subjects with different background may have dissimilar preferences that are not easily made explicit.

When we consider computational models, objective numerical comparisons would be desirable. In this case, performances are represented by sets of values. Various similarity or distance measures (e.g. absolute difference, Euclidean distance, etc.) can be defined over these, and it is not at all clear which of these is most appropriate musically. Likewise, it is not clear how to weight individual components or aspects (e.g. timing vs. dynamics), or how these “objective” differences relate to subjectively perceived differences. Agreed-upon methods for performance comparison would be highly important for further fruitful research in this field.

Common principles vs. differences

The models discussed in the previous sections aim at explaining and simulating general principles that seem to govern expressive performance, that is, those aspects of the relation between score and performance that seem predictable and more or less common to different performances and artists. Recently research has also started to pay attention to aspects that differentiate performances and performers’ styles (Repp, 1992; Widmer, 2003). The same

piece of music can be performed trying to convey different expressive intentions (Gabrielsson and Lindström, 2001), sometimes changing the character of the performance drastically. The CARO model (Canazza et al., 2004) is able to modify a neutral performance (i.e. played without any specific expressive intention) in order to convey different expressive intentions. Bresin and Friberg (2000) developed some macro rules for selecting appropriate values for the parameters of the KTH rule system in order to convey different emotions. The question of the boundary between predictability and individuality in performance remains a challenging one.

5.4 Conclusions

Quantitative research on expressive human performance has been developing quickly during the past decade, and our knowledge of this complex phenomenon has improved considerably. There is ample room for further investigations, and the field of computational performance research continues to be active. As the present survey shows, the computer has become a central player in this kind of research, both in the context of measuring and extracting expression-related information from performances, and in analysing and modelling the empirical data so obtained. Intelligent computational methods are thus helping us advance our understanding of a complex and deeply human ability and phenomenon. In addition, operational computer models of music performance will also find many applications in music education and entertainment – think, for instance, of expressive music generation or interactive expressive music control in multimedia applications or games, of quasi-autonomous systems for interactive music performance, of new types of musical instruments or interfaces that provide novel means of conveying expressive intentions or emotions, or of intelligent tutoring or teaching support systems in music education.

Still, there are fundamental limits that will probably be very hard to overcome for music performance research, whether computer-based or not. The very idea of a creative activity being predictable and, more specifically, the notion of a direct quasi-causal relation between the content of the music

and the performance has obvious limitations. The person and personality of the artist as a mediator between music and listener is totally neglected in basically all models discussed above. There are some severe general limits to what any predictive model can describe. For instance, very often performers intentionally play the repetition of the same phrase or section totally differently the second time around. Being able to model and predict this would presuppose models of aspects that are outside the music itself, such as performance context, artistic intentions, personal experiences, listeners' expectations, etc.

Although it may sound quaint, there are concrete attempts at elaborating computational models of expressive performance to a level of complexity where they are able to compete with human performers. Since 2002, a scientific initiative brings together scientists from all over the world for a competition of artificially created performances (RENCON, contest for performance rendering systems⁶). Their aim is to construct computational systems that are able to pass a kind of expressive performance Turing Test (that is, an artificial performance sounds indistinguishable from a human performance, Hiraga et al., 2004). The very ambitious goal proclaimed by the RENCON initiative is for a computer to win the Chopin competition by 2050 (Hiraga et al., 2004). It is hard to imagine that this will ever be possible, not only because the organisers of such a competition will probably not permit a computer to participate, but also because a computational model would have to take into account the complex social and cognitive contexts in which, like any human intellectual and artistic activity, a music performance is situated. But even if complete predictive models of such phenomena are strictly impossible, they advance our understanding and appreciation of the complexity of artistic behaviour, and it remains an intellectual and scientific challenge to probe the limits of formal modelling and rational characterisation.

⁶<http://shouchan.ei.tuat.ac.jp/~rencon/>

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