Gestural musical performance with physiological sensors, focusing on the electromyogram

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1 Introduction

Physiological computing has gained currency in recent years as the democratization of biomedical measurement technologies has facilitated take up in interactive computing systems. Signals from the human body can be detected by a wide array of sensors and digitized, providing computational systems information on individual identification, body states, and gross and fine limb movement. These signals have rich potential to be exploited for musical interaction – be it recording performer or audience state in ambient interaction, or capturing instrumentalists' volitional acts in gestural musical interaction. This chapter will focus on the potential of physiological interfaces to capture performer gesture to create embodied interaction with interactive music systems. The chapter is structured as follows: we begin with a brief history of the use of physiological signals in musical performance, noting the evolution of technology that has enabled the current interest. We introduce the range of physiological signals, and focus on one, the electromyogram, that reports muscle tension. We present techniques for using the EMG in music, including signal pre-processing in the form of feature extraction, and analysis in the form of machine learning. We discuss challenges of reproducibility and situate the EMG in multimodal context with other sensing modalities. We conclude by proposing gesture "power" as one low level feature that in part represents Laban's notion of "effort" to demonstrate the potential of the EMG to capture expressive musical gesture.

Human brainwaves were first measured by Berger in 1924, then sonified in the 1930s by physiologists Adrian and Mathews who translated signals measured with electrodes into audio signals to be heard through loudspeakers. In 1965, the American composer Alvin Lucier used brainwaves to activate acoustic percussion instruments in *Music for Solo Performer*. This work with biosignals was adopted by composers such as Richard Teitelbaum and David Rosenboom (Brouse et al., 2005), leading to the publication of the seminal book *Biosignals and the Arts: Results of Early Experiments* (Rosenboom, 1976). John Cage, in his large scale work, *Variations 7*, performed in 1966 in New York City as part

31 of the Experiments in Art & Technology (E.A.T.) 9 Evenings, called for "body sounds: heart,

32 brain, lungs, stomach." In 1974, Manford Eaton published Bio-Music, a manifesto calling for

33 a new biofeedback-based art in which the intentions of the composer are 'fed directly' to the

34 listener (Eaton, 1974).

35 With the arrival of early digital systems in the early 1990's, musicians began to interface

36 digitized biosignals with MIDI controlled synthesizers and computer music systems. The

37 IBVA[1] was created by Masahiro Kahata and was an early low-cost, portable digital EEG

38 device for art. The BodySynth[2], created by Chris Van Raalte and Ed Severinghaus was an

39 EMG music interface that was used performance artists such as Pamela Z and Laurie

40 Anderson. Ben Knapp and Hugh Lusted, researchers at Stanford University's CCRMA

41 created the BioMuse[3] in 1990, a DSP based biosignal-MIDI interface that read EEG, EOG,

42 and EMG (Knapp & Lusted, 1988). This system, and its subsequent minituarized incarnations

43 were adopted by the two authors for a series of music concert pieces. This facilitated

44 replication and rapid prototyping of systems that has facilitated ensembles such as the

45 BioMuse Trio, and use of biosignals in groups to conduct audience studies (Ortiz, 2012). The

46 increasing practicality of electronics resulted in use in media art contexts by Nagashima

47 (Nagashima, 2003). The information sharing in DIY communities has led to the publication

48 of designs for mechanomyogram (MMG) pickups[4] that have been used as the basis for

49 Donnarumma's Xth Sense[5] interface.

50 Advances in materials, electronics miniaturization, and manufacturing, have resulted in a

51 spate of consumer products that interface the human body to computing systems. These

52 products range from forms of biofeedback to aid in personal health monitoring[6], to products

53 that exploit insight from research in affective computing[7]. Sophisticated multichannel,

54 multimodal devices have been brought to market for hobbyists to control model drones by

55 gesture, and mundane tasks such as a virtual slide presentation clicker[8].

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[1] http://www.ibva.co.uk
[2] http://www.synthzone.com/bsynth.html
[3] http://www.biocontrol.com
[4] http://www.instructables.com/id/Measure-Muscle-Sounds!-Part-1%3A-Electronic-Board/
[5] http://www.xth.io/
[6] http://www.mindmedia.info/
[7] http://www.empatica.com/
[8] http://www.myo.com/

56   As the technologies became more accessible and accurate, the artistic focus of these projects

57   has shifted from an initial focus on biofeedback, to the notion of bio-control, to direct

58   physiological interfacing. Biosignals have broad musical potential. They range from their use

59   in augmenting traditional musical instrument performance, to copying existing instruments

60   for virtual, "air" instruments, to the creation of entirely new instruments in areas of

61   contemporary music and NIME. Free space gesture can be used to track non-instrumental

62   gesture, such as dancing and conducting (Marrin & Picard, 1998). All these types of musical

63   interaction can find application in music pedagogy and movement rehabilitation medicine.

64   **2   Biosignals**

65   The term *biosignals* is used to refer to physiological signals from living organisms, and that

66   manifest change in electrical potential across a specific cells, tissues, or organs. Tissues, such

67   as nerves, skeletal muscles, cardiac muscle and soft muscles, can generate electrical activity,

68   whereas others, like the skin and the eyes, are electrically passive and manifest potential

69   differences. The change in electrical potential offers a direct correlate of physiological

70   activity and depends on the entity being monitored. The most common biosignals are:

71   Galvanic Skin Response (GSR), which is the change of the skin's electrical conductance

72   properties caused by changes in emotional states like stress; Electrocardiogram (ECG/EKG),

73   a measurement of the electrical activity of the heart; Electrooculogram (EOG) is the

74   measurement of the Corneal-Retinal Potentials (CRP) across the eye; the

75   Electroencephalogram (EEG) monitors the electrical activity caused by the firing of cortical

76   neurons across the brain's surface; and the Electromyogram (EMG) which is the electrical

77   signal generated from activation and contraction of skeletal muscle fibers.

78   *2.1   The electromyogram*

79   Electromyography represents the isotonic, isometric and isokinetic muscle activity generated

80   by motor neurons (De Luca & Van Dyk, 1975). Isometric activity is muscle tension with no

81   change in muscle length (such as holding up weights without movement). Isotonic activity is

82   that where the change of muscle length and resistance is constant (push ups, curling dumb

83   bells). Isokinetic activity is that where the speed of movement and total tension are constant

84   but tension and length of muscle might change (fast pull-ups).

85 Motor Unit Action Potential (MUAP) refers to the activation of motor units. Motor units are
86 defined as the combination of a motor neuron and the muscle fibers it innervates. The MUAP
87 therefore is the electrical firing of a motor unit. This impulse is then transmitted from the
88 motor neuron to the muscle causing it to contract. The repetitive firing of a motor unit creates
89 an impulse train, which allows for what we perceive as sustained muscular contraction.

90 The main mechanisms that control the magnitude and density of the measured signal are the
91 recruitment and firing rate of MUAPs within the measured muscle in the area under study.
92 Individual MUAPs' have an average amplitude of $100\mu V$. The EMG signal that results from
93 the firing of individual MUAPs is stochastic in nature, reflecting the fact that the motor units
94 recruited in any gestures is constantly changing and has an amplitude range of +/- 5mV
95 before further amplification. Typical frequency contents of raw EMG signals for healthy
96 individuals ranges between 0 and 500 Hz, with dominant energy concentration in the 50-150
97 Hz range.

98 *2.2   Signal acquisition*

99 EMG signals are measured using electrodes which are conductive probes placed on the body.
100 When a biopotential is created by the contraction of the muscle, a differential amplifier picks
101 up the voltage changes between the otherwise equipotential areas created by the electrodes.
102 There are two main types of electrodes, invasive and non-invasive. Invasive electrodes are
103 needles or thin wires that measure activity of deep muscle fibers to be able to report the
104 activity of individual MUAPS. The placement of the electrodes is time consuming, must be
105 carried out by healthcare professionals. This, compounded by the relative discomfort wearing
106 them make them ill suited for musical performance practice.

107 Non-invasive electrodes make electrical contact with muscle cells through the surface of the
108 skin, providing surface EMG (sEMG). The most common electrodes are silver/silver chloride
109 wet gel electrodes. These types of electrodes have the best skin impedance values and are the
110 standard in medical practice. Altough they have been used extensively in music performance,
111 they require preparation of the skin and are prone to noise associated with movement
112 artefacts from the snap fasteners.

113 Dry electrodes have become increasingly common in high end as well as low-cost consumer
114 systems. The electrical contact with the skin via gold plated or other highly conductive metals
115 approaches, but does not equal that of gel electrodes. However, most designs incorporate

116 active pre-amplifiers immediately adjacent to the electrodes, making the output more robust
117 to electromagnetic interference and preventing the accumulation of noise along the signal
118 cable. This plus the ease of application and re-application make dry electrodes practical for
119 the use of biosignals in interactive arts practice.

120 Electrodes are typically placed at the middle portion of the studied muscle belly (Hermens,
121 Freriks, Disselhorst-Klug, & Rau, 2000). The most common placement of EMG sensors for
122 musical practice is in the forearms of the performer. This is a convenient place for the sensors
123 as it allows finger activity to be tracked via the forearm flexor and brachioradialis muscles
124 without an intrusive sensors, such as gloves, on the hands. Action potentials measured by
125 electrode pairs are processed using the differential amplification measuring voltage at the two
126 sites, subtracting the signals and amplifing the resulting difference. Any signal component
127 that is present at both electrodes is removed through common mode rejection. When using
128 wet electrodes, it is common practice to use an electrode placed in an unrelated area to act as
129 a reference ground, such as the ear lobe, or joints and other bony areas where no action
130 potentials are likely to occur.

131 Ambient noise such as that originating in mains lines and power sources can be problematic
132 when measuring biosignals. The alternating current (AC) frequency of mains electricity is
133 centered around 60 Hz (Americas) or 50 Hz (Europe). A notch filter can be used to attenuate
134 50/60Hz noise but good filter design is necessary since this overlaps with dominant energy
135 frequency of meaningful EMG, 50-150 HZ. The body itself can be a source of artifacts – the
136 heart is a strong muscle with a dominating EMG signal. This can interfere with EMG
137 measurements from limbs if the differential electrical measurement takes place across the
138 chest area.

139 *2.3   Signal processing and feature extraction*
140 The EMG signal has been compared in its richness to audio, making audio signal processing
141 and pattern recognition techniques potentially relevant in analyzing the biosignal. The EMG
142 is, however, ultimately not a continuous signal, but the sum of discrete neuron impulses. This
143 results in an aperiodic, stochastic signal that poses challenges to audio-based signal and
144 information processing. For interactive music applications to track performer state or gesture,
145 some kind of signal analysis needs to take place. This could typically be in two stages, first
146 feature extraction, followed by classification or mapping.

Feature extraction of the EMG entails analyzing the raw signal and using signal processing to create a representation containing salient higher level information about the nature of the gestural content. In this light, and given its signal complexity approaching that of audio, it can make use of techniques not dissimilar to those used in audio signal processing for music information retrieval. However, given the aperiodic stochastic nature of the EMG signal and the distinct nature of gestural content compared to musical content, the actual relevant signal processing techniques and high level information gleaned, will differ.

EMG signal features can be grouped into time domain (TD) and frequency domain (FD). Given the aperiodic nature of the EMG, there is no harmonic content for FD algorithms to extract, making them less useful for EMG analysis. The most straightforward TD feature is amplitude estimation, which reflects the level of muscle tension. This can be achieved in a number of techniques of differing sophistication. Simple amplitude estimation can be achieved as envelope following by smoothing, or low pass filtering of the raw EMG data. This can be done, for example, by taking the median of the signal over a time window, but introduces latency and lag of the length of the median window. Root Mean Square (RMS), the square root of the mean of the squares of samples in a time series, is a calculation of electrical power, and relates to constant force and non-fatiguing muscle contraction. Recursive Bayesian estimation or Bayes filter, is a probabilistic approach for estimating an unknown function over time using incoming measurements. The algorithm has been applied as a nonlinear estimator of EMG amplitude that improves the signal-to-noise ratio compared to RMS and considerably stabilizes the signal while remaining reactive to fast transients.

Other TD features that show good performance are Mean Absolute Value which provides energy information of the signal; Waveform Length which provides the cumulative length of the waveform over the time segment, and is related to the complexity of the EMG signal and whose values indicate a measure of waveform amplitude, frequency and duration all within a single parameter; and Willison Amplitude as a measure of frequency information of the signal, similar in nature to the number of zero crossings and related to the firing of MUAPs and muscle contraction force.

Frequency Domain features are based on statistical properties of the EMG signal's power spectrum density. FD features are usually used to detect neural abnormalities and muscle fatigue as it is related to motor unit recruitment. The most common FD features are: Median Frequency which is the frequency at which the spectrum is divided into two regions with

179   equal amplitude; Peak Frequency which is the frequency at which the maximum power

180   occurs; and the Mean Frequency, also known as Spectral Centroid, the center of gravity line

181   of the spectrum. FD features are useful for monitoring muscle fatigue as it results in a

182   downward shift of the spectrum as fatigue increases. It has been noted that FD features

183   perform poorly when compared to TD features for gesture classification tasks (Phinyomark et

184   al., 2013).

185   **3   Musical mapping**

186   Musical transformation of the EMG can take place at a number of different levels. The

187   physiological signal can be used directly as musical material in processes of sonification. The

188   EMG can be used in a control paradigm by mapping post-processed biosignal input directly

189   to sound synthesis parameters. The EMG data can be transformed into other discrete or

190   continuous presentations through machine learning.

191   *3.1   Sonification*

192   A common sonification technique is *audification,* where the raw data stream is upsampled

193   and fed directly to speakers or further processed by audio DSP modules. This is a direct way

194   of 'listening' to the signal itself which is characterized as a very low frequency sound with

195   noisy timbre. Once the signal is in the audio domain, it can be treated and transformed as any

196   other sound source.

197   The procedure is prone to artefacts. EMG hardware systems typically sample at a frequency

198   between 100Hz and 2kHz. When upsampling to audio sampling rates (44.1 or 48 kHz), this

199   will generate extra samples not present in the original signal, resulting in a sample-and-hold

200   effect where after a value will be repeated in the sound signal until a new EMG value arrives.

201   This translates into spurious high frequency content. A low pass filter at 200Hz is useful in

202   avoiding this problem.

203   *3.2   Mapping*

204   The raw EMG signal can be processed or subjected to feature extraction to provide lower

205   bandwidth data for discrete musical event and continuous sound synthesis control. Event

206   triggers can be derived from the rectified EMG amplitude. The high frequency, rapidly

207   varying nature of the signal, however, make it prone to false or multiple triggering. Using

208 smoothing techniques to filter transient spikes may introduce latency, causing system

209 responsiveness to suffer. A practical solution is to use a Schmitt trigger implementation,

210 where a hysteresis loop prevents an upward going event threshold to re-trigger until a lower,

211 downward going threshold has been attained.

212 The EMG is well suited for the continuous control of sound synthesis parameters. Multiple

213 channels can be used in conjunction with one another to generate series of events whose

214 sustaining sounds were shaped by subsequent muscle gesture. Gesture-parameter mapping

215 strategies, such as "one-to-many" mapping, where a single sensor input it mapped to multiple

216 synthesis parameters, or "many-to-one" where multiple sensor inputs might be combined to

217 control a single synthesis parameter (Hunt & Wanderley, 2003), are highly relevant to using

218 EMG in sound synthesis control. The amplitude feature, described above, is most commonly

219 used, with different low pass, or Bayesian filters to fine tune the smoothness and

220 responsiveness of the system. Calibration, by setting a minimum and maximum range of the

221 signal to utilize aids in eliminating a noise floor and allows focusing on a specific amplitude

222 range. Different response curves, from linear, to logarithmic, to exponential, can modify the

223 input/output relationship, creating a more natural feeling mapping between the exertion of the

224 performer and the facility of musical change.

225 The use of multiple EMG channels in a ring formation around the upper forearm is common

226 in myoelectric control systems and interactive performance applications. Each channel

227 provides information related to muscle activation in the area of each electrode pair. This

228 approach allows for the activation of opposing muscle groups to be monitored independently

229 and creates a more expressive feature space. Wrist flexion and extension can be effectively

230 tracked with just two channels of EMG on opposing forearm muscle groups. Four or more

231 channels around the forearm can provide information on hand rotation. Furthermore, it

232 makes the possibility to analyze the relationships in activation for each signal which can give

233 more detailed information of individual finger movements and hand gestures (Saponas et al.,

234 2009).

235 *3.3   Machine learning*

236 Beyond direct parameter mapping, the complexity of the EMG signal points to the potential

237 for using pattern recognition methods and information analysis techniques to both gain lower

238 level understanding of limb and sub-limb movement and elicit higher order representations of

239 musical gesture. These representations can be continuous in nature, or discrete in the
240 recognition performed.

241 Regression is one way for data analysis to produce continuous interaction by modeling the
242 relationship between a scalar dependent variable and one or more explanatory variables. It
243 transforms one continuous data stream into another information stream. Regression is useful
244 for dimensionality reduction of the EMG, either taking multiple streams of raw data to
245 produce information in fewer and more pertinent parameter dimensions for sound synthesis.

246 Discrete labels can be assigned to blocks of continuous EMG data, identifying gesture.
247 Machine learning classification techniques have been applied to EMG signals in biomedical
248 research for rehabilitation and basic prosthetics control applications. The requirements of
249 these scenarios are quite distinct from musical applications. Most of these applications use
250 classifiers like support vector machines (SVM) to distinguish between different hand
251 positions. The task is a supervised learning task where the classifier is trained with a series of
252 examples for subsequent linear, binary clustering. Ultimately, classification of static
253 positions can be thought of not as gesture recognition, but posture classification, where a
254 static steady state EMG signal from a number of EMG channels giving signatures of different
255 hand positions. The fact that these static positions, and therefore the classification result, are
256 achieved at the end of a gesture mean that in musical applications, this would be experienced
257 as a sort of latency, where the classifier reports on the gesture after it is completed.

258 The success criteria of gesture recognition in these different application areas is driven by
259 characteristics essential to the application. In prosthetics control, reducing error is primordial,
260 resulting in what might seem like relatively simplistic, binary controls. In music on the other
261 hand, the dynamic time based nature of musical performance, where musical expression
262 arises from subtle variation of gesture, generates a completely different set of needs in terms
263 of latency, continuity, and invariance. In music, a gesture needs to be recognized before it is
264 finished – a nontrivial challenge. We need to recognize without suppressing variation,
265 completely inverting the suppression of variation in canonical examples of data classification
266 such as handwriting or speech recognition. And finally, we seek forms of continuous
267 interaction with musical output such as sound synthesis, rather than discrete event triggering.
268 For the first challenge, techniques of "early recognition" can be implemented. For the second,
269 new adaptation approaches may be relevant, and for the third, regression techniques are
270 useful.

271   We created an early EMG gesture classifier using the K-Nearest Neighbors algorithm to train

272   and subsequently distinguish in real time six different hand gestures using two channels of

273   forearm EMG (A Tanaka & Fistre, 2008). Currently, we are applying recent advances in

274   machine learning to the EMG and other physiological signals. The use of Particle Filtering

275   techniques allows continuous reporting of recognition probability against a training set and

276   real time tracking of gestural variation against the reference template (B. Caramiaux,

277   Montecchio, Tanaka, & Bevilacqua, 2014). The temporal sensitivity, however, require

278   segmentation or some external signal indicating gesture onset.

279   ## 4   Musical gesture

280   The complexity of EMG data poses specific challenges and presents opportunities in live

281   interactive performance applications. A single data stream can embody information about

282   multiple parts of the body. A muscle group controls the movement of limbs below it: one

283   signal from forearm muscles can contain information multiplexing the movement of five

284   fingers. Meanwhile the EMG signal may not return to a rest state in between a sequence of

285   gestures. One gesture may begin before the previous one ends. The EMG signal, therefore,

286   may encapsulate information on multiple parallel, *complex gesture*, as well as a sequence of

287   serial, *compound gesture*. This creates the need for techniques of gesture segmentation and

288   decomposition. In addition to distinguishing constituent gesture primitives within compound

289   and complex gestures, fundamental challenges exist to differentiate between voluntary,

290   involuntary, and incidental physical behavior. These qualities have a bearing on musical

291   applications, the kind of gesture recognition techniques and sound synthesis mappings that

292   can be applied.

293   The feature extraction and data analysis techniques described above allow the music

294   interaction researcher to process the richness of the EMG signal to make it more usable.

295   However, because of the number of different muscle groups solicited for making any action,

296   there does not exist a direct correspondence between muscle exertion and resulting limb

297   movement. This means that there is not a direct, deterministic relationship between muscle

298   states and gesture, making movement representation uniquely via EMG difficult. Two aspects

299   contribute to this problem: the fact that multiple different combinations of muscle tension

300   could result in the same gesture, and the fact that muscle tension may not result in movement

301   at all.

4.1   Gesture without movement

The fact that EMG measures isotonic and isometric activity means that there is not a deterministic link between limb movement and muscle tension. Muscle tension may be exerted without corresponding limb movement. Conversely, certain gross gestures could take place with little muscle contraction. While this makes prediction of movement gesture difficult, these characteristics of the EMG signal make it uniquely suited for detecting gesture preparation. This makes the EMG an interesting sensing modality that offers complementary information to physical sensors that report on movement after it is performed. In this sense, the EMG is useful in contexts of multimodal interaction.

4.2   Redundancy and ambivalence

While the EMG offers these unique opportunities, these qualities can make it challenging to implement in scenarios or studies with non-specialist users. The "same" (or highly similar) gross movement can be made by invoking any number of muscle tension trajectories. This can be thought of like the multiple degrees of freedom problem found in robotics in multi-joint articulation and is formalized by the neurophysiologist Nikolai Bernstein in motor control theory. This poses a distinct problem in applying the machine learning techniques described above. Different people will invoke different combinations of muscles to perform what to an observer is the same gesture. Complicating matters further, a single subject may perform the same movement with slightly different muscle tension profiles each time. This poses the problem of gesture reproducibility. Additionally, repeated performance of a given set of gestures will lead to muscle fatigue which adds further aperiodic variations to the measured signal. While FD features can be used to monitor the evolution of fatigue over time, the effects of fatigue in the signal's amplitude are not directly correlated.

We have conducted experiments that study the ability of lay users to learn and copy gestures (Baptiste Caramiaux, Donnarumma, & Tanaka, 2015). We designed gesture vocabularies that focused on different muscle groups in simple lower arm and wrist movement tasks. We provided auditory feedback that allowed the subject to monitor their gesture during execution. Later, in separate work with more complex gestures, we have observed that visualization of multiple channels of EMG signal aid the subject in replicating a gesture with sufficient muscular similarity to be successfully classified by machine learning techniques.

332   *4.3   Multimodality*

333   The ability of EMG to report on gesture without movement, alongside the degrees of freedom

334   problem, mean that the EMG is well suited for use in context with other sensing modalities.

335   Multimodal interaction in HCI takes advantage of the integration of different input modalities

336   to enhance the information bandwidth with an interactive system. The EMG, reporting on the

337   *intention* and preparation of a gesture provides a complementary input modality to inertial

338   sensors or motion capture systems that report on the physical movement result of that gesture.

339   We have used muscle sensing alongside optical motion capture and accelerometer sensing to

340   look at this sensor complementarity in the execution of musical gesture (Donnarumma,

341   Caramiaux, & Tanaka, 2013). We observed several different relationships between the

342   sensing modalities: *synchronicity* when certain segments of the sensor data are coincident

343   across modalities; *coupling,* where different modalities vary in similar ways in different

344   articulations of the same gesture; and *correlation*, where the actual relationship between

345   different sensing modalities shifts during the course of the gesture.

346   **5   Expressivity**

347   These relationships of multimodal interaction put EMG in context for providing an

348   expressive dimension to gestural interaction in music. The complementary sensor modalities

349   could be used in an orthogonal fashion, where the same muscle tension trajectory could mean

350   different interactions on the music based on different gross positions detected by another

351   sensing modality. We have explored techniques for multi-modal interaction to distinguish

352   similar muscular gestures in different points in space (Atau Tanaka & Knapp, 2016).

353   Biosignals can also be seen as extremely low latency information about gesture. The EMG

354   reports a neural command that causes muscle tension, resulting in limb movement. It reflects

355   the intention of gesture, and in this regard is at the opposite end of movement production than

356   a sensor such as an accelerometer that reports on physical artifacts resulting from gesture. A

357   classical sensor, then, is at the "output" of a gesture while the EMG is a signal that is the

358   "input" to a gesture.

359   The execution of gesture can take place in free space or with "boundary objects". These

360   boundaries could be objects one grasps, like a physical implement or instrument, or a surface

361   that offers resistance to movement. Boundary objects therefore offer isotonic gestures

362   resistance against which they may act, facilitating the adjustment of exertion. This provides a

363 form of feedback that facilitated task performance in our study (Baptiste Caramiaux et al.,
364 2015). Through this study, we identified the abstract notion of gesture "power" which could
365 be tracked by the EMG and detected in certain signal features of the EMG. On surface
366 gestures, the notion of power corresponds to exertion, or effort. This creates interesting links
367 with the concept of "effort" in Laban Movement Analysis movement (Silang Maranan et al.,
368 2014).

369 The characteristics of the electromyogram signal make it uniquely well suited for capturing
370 expressive musical gesture. The challenges it poses – the degrees of freedom problem, and
371 the lack of direct link between signal and resulting movement – provide the richness in the
372 signal that cannot be gleaned from other, physical sensors. The signal is at the very source of
373 gestural activation, making it now just responsive, but able to report on musical intention. It
374 is ultimately not an external observation of the physical output of musical movement, but the
375 body's own signal for creating musical gesture.

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