Musical Notation and Fine Motor Skills when Playing the Soprano Recorder: Making A Neural Network Lift a Finger

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Abstract

Most studies on notation-fingering mapping used the piano where one finger covers one key to produce one tone. This study used the recorder as a model, where learning of finger combinations is needed to produce one tone. In three simulations, a 13 x 5 x 5 x 10 three-layer feedforward neural network was required to transform a binary spatial representation of a musical notation of the chromatic C' scale on the stave into the appropriate fingering output on the ten holes of the Soprano recorder. The network could play random sequences of tones and 'Amazing Grace' successfully. It was not the case that musical notes were gradually grouped into large chunks, as assumed, but instead the network just grouped pairs of tones and halftones, and worked harder on adapting the motor output to the properties of the instrument. An initial network with few internal nodes learned to keep all fingers down (activation), but when the number of internal layer nodes matched output nodes, the network could develop an activation/inhibition representation in the connections between internal layer and output nodes to keep fingers down, but also lift them. A robust finding in all three network simulations was that the activation and inhibition pattern indicating motor flexibility showed particularly in the lower part of the Soprano Recorder. This was explained with statistical learning, as fingers in the lower part of the instrument could stay in place for low pitch tones, but needed to be lifted for high pitch tones, while in the upper part of the instrument, fingers could stay in place most of the time. Hence the network systematically developed motor flexibility on a localized part of the spatial scale of an instrument determined by statistical learning.

1. Introduction

Playing an instrument, like producing a drawing has a strong motor component (Braswell & Rosengren, 2008; Lange-Küttner, 1998; Lange-Küttner & Vinter, 2008). The capacity to draw requires flexibility, which can refer to both mental flexibility (Karmiloff-Smith, 1990), and/or flexibility in fine motor skills (Vinter & Perruchet, 2002; Vinter & Marot, 2007). A graphic syntax would specify a 'grammar of action' (Goodnow & Levine, 1973) needed to conceptualize the space on the sheet of paper in order find the location from where to start with the drawing movement, and how to progress (e.g. top-to-bottom, left-to-right) (Vinter, Picard, & Fernandes, 2008). Likewise, a traditional musical instrument is an object with a particular physical design to which the player must adapt his fine motor finger movements in order to produce a sound (Merrill, 2004). The oldest instrument appears to be the flute dating back to the neolithic age (Zhang, Harbottle, Wang, & Kong, 1999). The output of a flute is one tone at a time, and in this way it is more simplistic than e.g. a piano keyboard where two independent melodies and several notes in a chord can be generated by the two hands. However, the fingering rules of a flute to produce one note are more complex: A keyboard player needs to press just one finger in order to produce the equivalent of one note in a one-to-one mapping. But to achieve the same effect e.g. on a transverse flute or a recorder, a combination of several fingers needs to be used. Hence, while a flute has the physical constraint that it cannot produce chords, it nevertheless requires sophisticated fine motor skills to produce just one tone and, importantly, these patterns do not always follow a logical progression like on the keyboard.

We were also interested in the *weighting* of the processes involved in music reading vs. motor output. What would be the weighting of these two processes in successful performance ? Learning motor control is assumed to involve the cerebellum in supervised error-based learning, the subcortical areas of the thalamus and basal ganglia in reinforced reward-based learning, and neocortical areas in unsupervised learning (Doya, 2000). Indeed, neuroimaging of piano players vs. non-musicians showed a large brain network of cortical and subcortical areas which contributed to keyboard playing, but the largest activated homogeneous brain areas were the sensori-motor and the parietal cortex (Landau & D'Esposito, 2006; Parsons, Sergent, Hodges, & Fox, 2005), indicating great importance of fine motor skills in interaction with a spatial layout. Piano players showed the same brain networks as non-musicians who learned to play, but they were more intensely used, as they showed increased activation while learning, and increased deactivation in repetitive performance (Landau & D'Esposito, 2006).

Nevertheless, a purely sensori-motor account would not account for several other effects related to learning to play a musical instrument. Kindergarten children have shown significant long-term improvements in spatial-temporal reasoning ability, but not pictorial memory, following music training on the keyboard (Bilhartz, Bruhn, & Olson, 1999; Rauscher & Zupan, 2000). Music making practice could also improve verbal memory, but again not visual memory (Chan, Ho, & Cheung, 1998; Ho, Cheung, & Chan, 2003). This is the more astonishing, as in the mature brain, imagining to play an instrument and actually playing on it have a large, albeit not complete overlap (Solodkin, Hlustik, Chen, & Small, 2004).

Ockelford (2004) presumed that in the mature adult brain, pattern recognition of notes would follow Gestalt principles such as similarity and saliency as well as categorization. Sight-reading of musical notes may be a similar process as reading of words in written language (Sergent, Zuck, Terriah, & MacDonald, 1992; Sluming, Brooks, Howard, Downes, & Roberts, 2007): In reading, the ‘grain size’ of word structure can become larger with extended practice (Lange-Küttner, 2005; Samuels, Miller, & Eisenberg, 1979; Ziegler & Goswami, 2005). Individual differences showed a trade-off between neural representations and practice effects: There is not only a link of reading disorders and motoric hyperactivity in boys (Willcutt, 2000), but male keyboard players often had a smaller cerebellar brain volume, yet showed large practice effects, while female musicians had the larger cerebellar volume, but did not show practice effects (Hutchinson, Lee, Gaab, & Schlaug, 2003), possibly because of a greater past practice history. Thus, the categorization of the musical notes by the neural network will be inspected to test whether the successful network would have used larger groupings of notes.

Learning to play a musical instrument in children is almost never carried out without tuition by a teacher, and both reinforcing, or critical, teacher feedback is given regularly in music lessons (Duke & Henninger, 2002; Schmidt, 1995), while self-regulation appeared to be inefficient and limited to repetition in children (McPherson & Renwick, 2001). Hence, most children may not use motor or visual imagery when learning to play an instrument, but would benefit from the exercise of mapping the reading of musical notes to an action plan involving the development of a sensori-motor spatial syntax for the motor output (Haueisen & Knösche, 2001; Stewart et al., 2003).

We thus modelled playing the Soprano recorder in several supervised network models, and report both one of the initial ones and the successful ones. The ‘network recorder’ was taught to read the musical notations of the chromatic C scale, and translate these into key presses. In the current simulation all notes from a low C (C4) to a high C (C5) were used, including sharps and flats. A sharp note is one semitone higher than it’s natural note, and a flat note is one semitone lower. Either a sharp or flat label can be applied to a note to produce the same semitone, e.g., H^b is sometimes called A#, and both is technically valid.

2. Learning to play the recorder

This study used the neural network simulator T-learn (McLeod, Plunkett, & Rolls, 1998; Plunkett & Elman, 1997). This software did not allow to simulate unsupervised learning, which may be desirable given the importance of independent exploration (Schlesinger & Parisi, 2007), but as mentioned before, children usually learn to play with error feedback from a music teacher. Thus, supervised neural learning with backpropagation of error was deemed appropriate. A feedforward neural network was designed to model learning of fine motor skills (Iberall & Fagg, 1996).

The network input consisted of 13 input nodes, covering C, C#, D, E, E^b, F, F#, G, G#, A, H, H^b and C.

Fig. 1 The Chromatic Scale of C4 to C5 (E^b is noted as D# and H^b is noted as A#).

The layered musical notation system of a stave (see Fig. 1) was transformed into a spatial binary pattern of 13 input nodes (six nodes for five lines plus a ‘help’line for the lower C, five nodes for five spaces in between, and two nodes to define the tone whenever a note was either flat or sharp). The placement of the note on the stave was represented by an activation of 1. One input node was active at a time, and for C, E, F, G and H sharpness or flatness was indicated with a second activated input node (see Fig. 2).

1	0	0	0	0	0	0	0	0	0	0	0	0	**C**
1	0	0	0	0	0	0	0	0	0	0	0	1	**C#**
0	1	0	0	0	0	0	0	0	0	0	0	0	**D**
0	0	1	0	0	0	0	0	0	0	0	1	0	**E^b**
0	0	1	0	0	0	0	0	0	0	0	0	0	**E**
0	0	0	1	0	0	0	0	0	0	0	0	0	**F**
0	0	0	1	0	0	0	0	0	0	0	0	1	**F#**
0	0	0	0	1	0	0	0	0	0	0	0	0	**G**
0	0	0	0	1	0	0	0	0	0	0	0	1	**G#**
0	0	0	0	0	1	0	0	0	0	0	0	0	**A**
0	0	0	0	0	0	1	0	0	0	0	1	0	**H^b**
0	0	0	0	0	0	1	0	0	0	0	0	0	**H**
0	0	0	0	0	0	0	1	0	0	0	0	0	**C**
L	***S***	***L***	***S***	***L***	***S***	***L***	***S***	***L***	***S***	***L***	***F***	***Sh***	

Fig. 2 Data Input of the Pattern Associator Network (L = stave line, S = stave space, F = flat, Sh = sharp)

The network had 10 output nodes, corresponding to 10 holes of the English recorder fingering chart, see Fig. 3. The binary coding was 1 for a finger covering a recorder hole, and a 0 if a finger was to be kept lifted above the hole. The lower the tone on the stave, the more holes on the recorder needed to be kept shut.

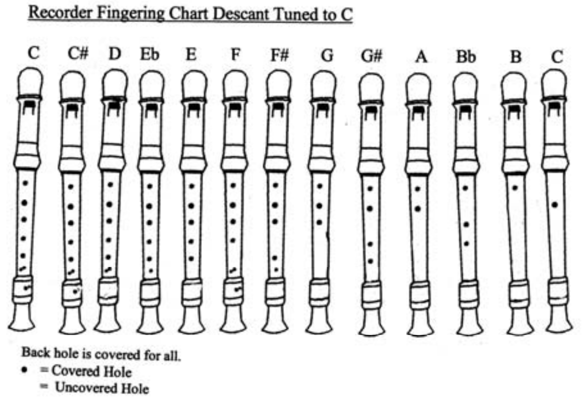

Fig. 3 Fingering Chart for Soprano Recorder (dark dots = finger down, the 10th hole on the back is always covered)

An initial 13 x 3 x 3 x 10 three-layer feedforward network was identical to the successful neural network in Fig. 4, except for 3 instead of 5 hidden nodes in each of the two hidden layers. A bias node was connected to all hidden layers and the output nodes, but is not displayed in the network architecture. The bias node ensures that the network stays activated, like some ongoing nervous activity in the absence of external stimulation. The initial network did already show the same categorization of the input, i.e. mostly pairwise clustering of tone and semitone in branches of a hierarchical tree structure (without illustration), which had not become different in the subsequent network models with more nodes in the hidden layers. This first reported neural network and all subsequent ones were trained with a learning rate of 0.1 and a momentum of 0.9. Seeding was random and the network was trained sequentially with replacement. The backpropagation RMS error was logged every 100 sweeps.

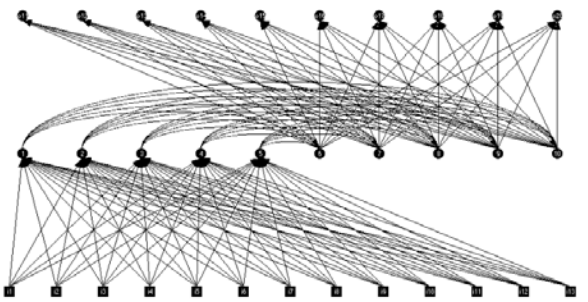

Fig. 4 13 x 5 x 5 x 10 Neural Network Architecture (The second hidden layer is displayed besides the first hidden layer)

This neural network already learned and the error rate was reduced, however, it did not learn the semitones, and the error rate did not drop much below .50 even with extended practice of 10,000 sweeps, see Fig. 5.

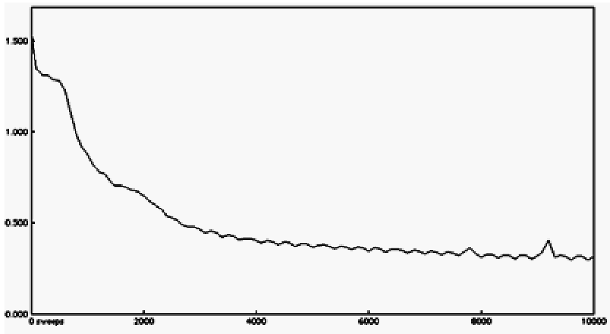

Fig. 5 Error Reduction Display (Learning Curve) of a 13 x 3 x 3 x 10 Three-Layer Feedforward Network

Why did this neural network model fail to be really successful ? Hinton diagrams (Hinton, 1986) show us the activation and inhibition patterns of the connections between nodes. Fig. 6 shows the activation patterns between input and first layer in the upper left corner, between first and second hidden layer in the middle square, and the connections between the second hidden layer and the output nodes in the lower right rectangle. As can be clearly seen in Fig. 6, the connection weights of the input nodes i1 to i3 denoting the lowest tones, and the i12 and i13 input nodes which defined the semitones, with the first hidden layer nodes 1-3 showed some inhibition. To a much larger extent this inhibition was apparent in the connection weights between first and second hidden layer. However, the majority of the connections weights between the second hidden layer nodes 4 to 6 and the majority of the output nodes 7 to 16 showed considerable to high activation.

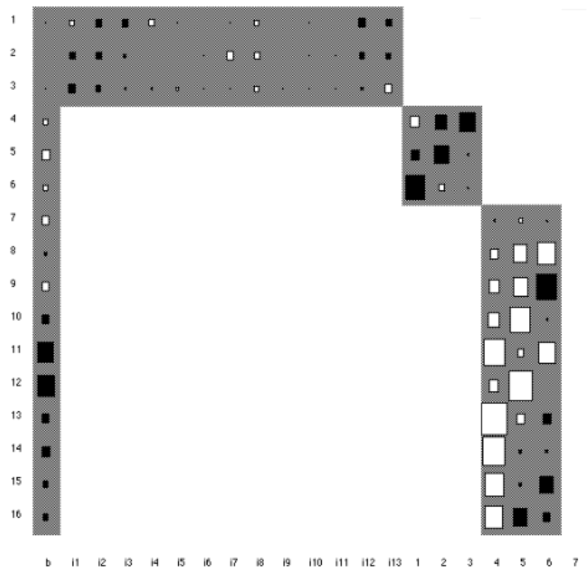

Fig. 6 Hinton Diagram (dark squares = inhibition, white squares = activation) of the 13 x 3 x 3 x 10 Three-Layer Feedforward Network after 10,000 swipes

Hence, these internal representations give the impression as if the neural network has established some division of labour between the two hidden layers, which allowed a very busy motor output.

However, the error would still did not drop below .40 in a 13 x 4 x 4 x 10 three-layer feedforward neural network, i.e. when an additional nodes was added to each hidden layer, after 10,000 sweeps, even though already all semitones except F# were mastered. The network needed at least two layers of five hidden nodes in order to play all semitones : The neural network which successfully learned to match all musical notations inclusively all semitones with the appropriate fingering on the Soprano recorder was a 13 x 5 x 5 x 10 feedforward network, see Fig. 7. After 5,000 swipes, the error rate had dropped to about .10, a widely accepted benchmark for success (Plunkett & Elman, 1997), see Fig. 5. It appeared to be the case that while the first hidden layer in the network would now process the lower pitch tones and the semitones in the input nodes more correctly, the second hidden layer would transform the notation into an appropriate fingering.

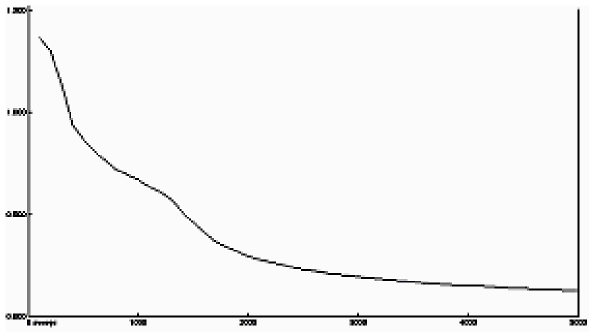

Fig. 7 Error Reduction Display (Learning Curve)

One of the problems of the networks with fewer hidden nodes was that it was difficult to achieve a balanced pattern of activation and inhibition in the fingering output, i.e. the flexibility to press down a finger or keep it lifted. The Hinton diagram in Fig. 6 now shows a nearly perfect balance of activation and inhibition in the connection weights between the nodes 9 and 10 of the second hidden layer with all output nodes, which resembles a representation of the Soprano recorder fingering chart, while the remaining nodes of the second hidden layer appear to process further information about the input. One could presume that five hidden nodes were necessary in order to represent one half of the Soprano recorder with its ten holes. The lower part of the Soprano recorder, which is mainly served by the right hand in ‘real life’, appeared to trigger an especially strong balanced activation pattern.

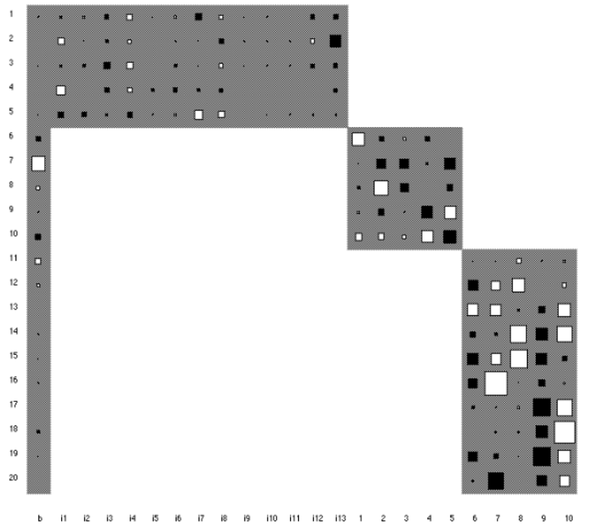

Fig. 8 Hinton Diagram (dark squares = inhibition, white squares = activation) of the 13 x 5 x 5 x 10 Three-Layer Feedforward Network after 5,000 swipes

The same simulation was run a second time in order to replicate this finding. The activation-inhibition balance in the lower part of the recorder was now moved from nodes 9 to 10 (*on the right*) in the second hidden layer to nodes 6 to 7 (*on the left*) in the second hidden layer, see Fig. 7. One could even presume, that while in the first simulation, the lower part of the Soprano recorder was served by one hand, in the second simulation, these operations were carried out by the other hand. The middle part of the Soprano recorder, which was already activated in the first simulation, had now become even more activated in the replication, and this had broken up the vertical continuity of the representation of the fingering chart in the connection weights.

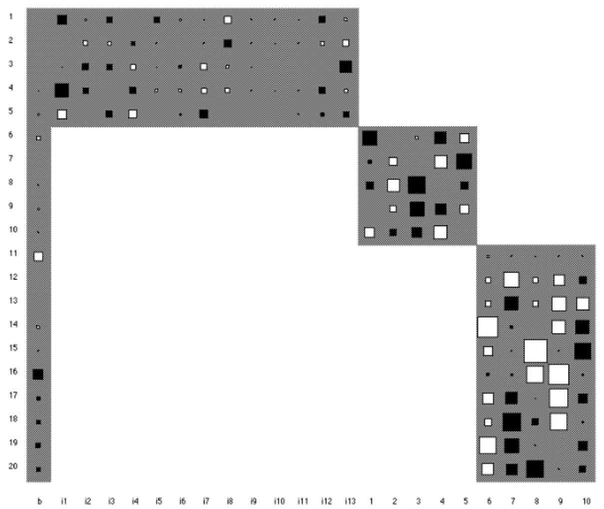

Fig. 9 *Replication*: Hinton Diagram (dark squares = inhibition, white squares = activation)

To test the neural network further, the trained network was given a longer input pattern which represented the sequence of the musical notes in the song ‘Amazing Grace’, using the same notation as in the training file. However, this time there was no teacher file in the simulation, which before had specified the matching fingering pattern for each musical notation of a tone on the C-octave. Fig. 10 shows that the trained neural network initially showed a slightly higher error, but could successfully produce the correct fingering for the Soprano recorder to play the tune ‘Amazing Grace’.

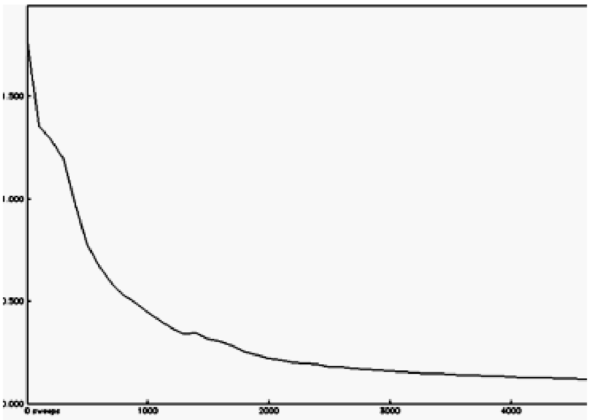

Fig. 10 Error Reduction Display (Learning Curve) for the trained Neural Network reading the musical notation and playing ‘Amazing Grace’ on a Soprano Recorder

The Hinton diagram (Fig. 11) shows that connection weights from the second hidden layer to the output layer were again well balanced in terms of inhibition and activation in the lower part of the fingering chart, but in a reversed fashion compared to the replication. The middle part now also shows more finger flexibility.

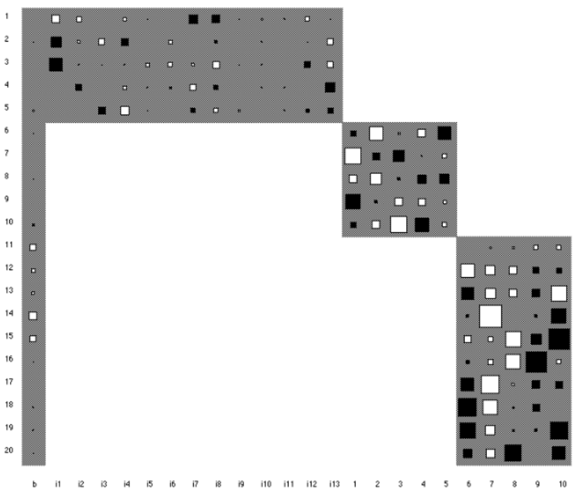

Fig. 11 Hinton Diagram of the trained Neural Network which learned to play ‘Amazing Grace’

Discussion

The current pattern associator networks demonstrated that the networks learned to read a binary musical notation and to produce the correct fingering in the output. The network did not categorize the notes into larger chunks when it became more successful in error reduction, it only grouped tones with halftones in a pairwise fashion. Instead, it was necessary to design as many internal hidden layer nodes as there were output nodes (Soprano recorder holes). With this architecture the network could develop a finger activation and inhibition system in the connections between internal representations and the motor output which allowed the network to ‘lift a finger’.

The input was conceptualized as a binary spatial pattern of the stave, where the musical notation indicated the pitch of the tone (the lower on the stave in spatial terms, the lower the pitch of the tone in auditory terms), as well as whether the tone was a semitone or not, and whether the tone was flat or sharp. The architecture was a three-layer feedforward network with 10 output nodes representing the 10 holes of the Soprano recorder. It was assumed that the first hidden layer in the network would allow to categorize the input, while the second hidden layer would transform the musical notation into a motor output on the instrument.

An initial, less successful neural network showed high inhibition in the first hidden layer, and high activation in the second hidden layer connected to the output. This would imply that the network learned to cover the holes of the Soprano recorder, but produced a high amount of errors. That the subsequently successful networks needed 5 hidden nodes each in the two hidden layers may have to do with the segmentation of the recorder into a lower and an upper part with 5 holes each, served by one hand each, respectively. Three simulations were run with this 13 x 5 x 5 x 10 network, the original simulation, a replication of this training study, and an application of the training to the tune ‘Amazing Grace’. To reduce errors, the network learned fine motor skills, i.e. in particular the flexibility to not just press fingers down, but also to keep some fingers lifted. The network had achieved this objective successfully in all three network simulations by paying attention to the lower part of the Soprano recorder, where activation and inhibition were well balanced. This indicated a localized motor flexibility of finger pressing and finger lifting. And indeed, when playing the Soprano recorder, the production of the tones with lower pitch requires pressing the fingers down on both parts of the recorder, e.g. playing the lower C requires all holes covered and all fingers down. However, the tones which are higher in pitch most often require lifting fingers only on the lower part of the instrument, while the fingers in the upper part are more likely to stay in place. Thus, when playing music on the recorder, it is statistically more likely that the fingers on the lower part of the instrument need lifting than the fingers on the upper part of the instrument. Hence, while motor output as such required 'just' activation of internal representations, the development of motor flexibility required statistical spatial learning (e.g. Fiser, Scholl, & Aslin, 2007).

In summary, the networks needed to segment the upper and the lower part of the Soprano recorder, started to develop motor flexibility where the most frequent finger lifts where required and then after training, finger flexibility appeared to gradually extent with practice upwards across the recorder to holes where fewer finger lifts were required. Without this upper/lower segmentation the neural network appeared to produce a motor output (keeping holes covered), without developing a syntax (Vinter et al., 2008), i.e. being able to know where and how to start with error reduction (which holes not to cover). Anecdotal evidence of music teachers did indeed confirm that young children find it difficult to keep all fingers down to cover the holes completely, i.e. without producing an air leak which would distort the tone, before flexibility and ease of finger movement develops.

Another important aspect was that the network could swap the left and right hand side, as if it was once a right hander and once a left hander. This corresponded to a neural network which also showed little spatial side bias when searching for an object on the left and the right hand side of a spatial display (Lange-Küttner, in press; Thelen, Schöner, Scheier, & Smith, 2001). Also musicians showed varying spatial bias (Landau & D'Esposito, 2006) and increased inter-hemispheric connectivity via an enlarged corpus callosum (Ridding, Brouwer, & Nordstrom, 2000), especially in male mature musicians (Lee, Chen, & Schlaug, 2003), as they might have had to counteract a usually more lateralized male brain.

Furthermore, chunking of musical notes did not occur except for pairing of tones and semitones. Keeping notes relatively individual could have been a reaction towards the task to play repetitively sequenced notes, but chunking also did not emerge when the network played a tune where notes followed a melodic sequence. Instead the network worked harder to adapt the motor output to the properties of the instrument, as instead the finger placements needed grouping to produce a single tone. This adaptation process towards the instrument as an object with physical constraints is often underestimated. Merrill (2004, p.29) comments on previous neural network modelling that 'an interesting pattern in the existing body of work is the minimal attention paid to the form of the physical device in these learning and classifying systems'. He found that people were conservative about the setting of their synthesizers, and musicians would develop a special relationship with their instrument, e. g. BB King would name his favourite guitar 'Lucille' and Yo Yo Ma his cello 'Petunia' (Merrill, 2004, p. 31). It may be that the longevity of motor memory (Baddeley, 1999) developed in interaction with the physical specificities of an instrument contributes substantially to this perception. The importance of motor processes was also obvious in a differential training of trombonists students, where not surprisingly, either motor or mental practice was better than no practice, but more importantly, a combination of *both* motor and mental practice was better for performance than mental practice alone (Ross, 1985). Mastering random (as in modern music) and logical sequences (as in traditional music) is more demanding than producing repetitive and relatively monotonous motor sequences (Landau & D'Esposito, 2006, p. 256) in pianists. However, the current recorder networks needed to learn complex synchronous fingering combinations even though the repetitive, gradually ascending-in-pitch sequence of tones was relatively easy, and having mastered this, did not need to develop notational categorizations to play the relatively predictable melodic phrases of 'Amazing Grace'. Piano players would be equally challenged with regards to complex fingering combinations only when playing chords, and then clustering of musical notes would become necessary.

Toomela (2002) showed in a large developmental study that astonishingly the only significant new predictor for drawing advanced visually realistic objects were fine motor skills which replaced chronological age as performance predictor. Fine motor skills might also be correlated with attention to fine detail (Lange-Küttner, 2000), e.g. females pay more attention to fine detail in drawing, which leads to better performance in contour drawing of small parts (Lange-Küttner, Kerzmann, & Heckhausen, 2002), but also in mental rotation where it leads to lower performance than in males, as vector rotation is required (Geiser, Lehmann, & Eid, 2006; Hughdahl, Thomsen, & Ersland, 2006). Vectors are spatial axes which segment space independently of individual locations in a linear fashion (Lange-Küttner, 1997, 2004, 2008). It seems that this current neural network required both, flexibility in the control fine motor movement, but applied to a localized part of a spatial axis identified by its statistical properties, i.e where action affordances were clustered.

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