Let Us Dance Just a Little Bit More — On the Information Capacity of the Human Motor System

Teemu Roos  
Helsinki Inst. for Inform. Tech. HIIT  
University of Helsinki  
Helsinki, Finland  
Email: {firstname.lastname}@hiit.fi

Antti Oulasvirta  
Computer Graphics Department  
Max Planck Institute for Informatics  
Saarbrücken, Germany  
Email: oantti@mpi-inf.mpg.de

Laura Leppänen and Arttu Modig  
Helsinki Inst. for Inform. Tech. HIIT  
University of Helsinki  
Helsinki, Finland  
Email: {firstname.lastname}@hiit.fi

Abstract—Fitts law is a fundamental tool in measuring the capacity of the human motor system. However, it is, by definition, limited to aimed movements toward spatially expanded targets. We revisit its information-theoretic basis with the goal of generalizing it into unconstrained trained movement such as dance and sports. The proposed new measure is based on a subjects ability to accurately reproduce a complex movement pattern. We demonstrate our framework using motion-capture data from professional dance performances.

Index Terms—Fitts’ law, information capacity, human motor system, human–computer interaction

I. INTRODUCTION

The purpose of the human motor system is to transform electro-chemical signals in the nervous system into physical movement. The dominant paradigm for studying the information capacity of the human motor system is based on the pioneering work by Paul Fitts in the 1950s [6], [7], [16]. Its primary application is the analysis of user interfaces in human–computer interaction [10], [15], [17], where information throughput is formalized in terms of a standard Gaussian channel, see [4], has been immensely popular since it enables the comparison of performance across situations with different characteristics. The index of performance (IP) defines the information throughput in units of bits per second (bps):

$$IP = 1/b.$$  

(2)

IP is argued to be a good metric because, as observed by Fitts, and later many others, it tends to stay relatively constant over a broad range of values of $D$ and $W$ [15], [17], providing a natural basis for comparison of pointing devices. The mouse, for example, typically reaches ca. 4 bps, and joystick ca. 2 bps [15].

The motivation for the present work is that important aspects of the information potential of human motor system are not covered by the Fitts’ law paradigm, and that consequently, the capacity of human motor system is systematically underestimated — insofar as the said paradigm even attempts to estimate the capacity of the whole motor system. In fact, Fitts’ law and its generalizations are constrained to aimed movements of one (or few) body part(s) in target conditions that are prescribed to a high degree by the experimenter. This has three important implications. Firstly, the “information” that is being measured is tantamount to the subject’s ability to motorically conform to extrinsic constraints, excluding entirely free movement, i.e., movement produced irrespective of its absolute position in respect to perceivable environmental constraints. Such movements are important in many skilled activities, such as dance and sports. The issue of
underestimation is exacerbated by the empirical paradigm, which utilizes very simple repetitive movements with simple trajectories (see [1]). Secondly, Fitts’ law does not account for information in simultaneous movement of multiple body parts (for an exception, see [2]). There are 640 muscles, 200-300 joints, and 206 bones in the human body. Obviously we are not able to independently control each one of them, but some separation is possible; for instance, the thumb and the index finger can be moved relatively independently of each other and the three other fingers [3]. Thirdly, most skilled activities involve compound tasks, with multiple aimed and other types of movement performed simultaneously and sequentially. Due to these three limitations, we argue that the Fitts’ law paradigm is not suitable for the study of skilled motor action; i.e., precisely the ones that can be expected to contain the most information!

Extending Fitts’ definition, we define information capacity in terms of the ability to accurately reproduce any previously performed movement pattern. An infant is a good example of low information capacity. At any moment in time, the infant’s movement can appear complex, but the fact that he or she cannot reproduce it at will means that the motor system lacks the information capacity to do so.

Our formulation is based on subjects performing arbitrarily complex un-prescribed movements; Fitts’ paradigm, involving only experimenter-defined pointing tasks, is a special case. The formulation can accommodate movement of any duration and composition and involving contributions of any part of the body.

The rest of the paper is organized as follows. In Sec. [II] we describe a measure of shared information between two movement sequences. The data and the preprocessing steps are detailed in Sec. [III] and the results of the experiments are summarized in Sec. [IV]. To conclude, in Sec. [V] we discuss potential applications and outline future work.

II. Information Measure

To quantify the information capacity, it is necessary to separate the controlled aspects of the performed sequence of movements from the unintentional aspects that are unavoidably present in all motor responses. As discussed above, the strictly defined range of admissible performances in Fitts’ paradigm has a similar function: it rules out apparently complex, uncontrolled (random) sequences of movements. Instead of restricting the allowed movements, we propose to solve this task by having a sequence repeated as exactly as possible by the same subject. This makes it possible to obtain an estimate of the variability of the two patterns, and subtract the complexity (entropy) due to it from the total complexity of the repeated performance. In other words, information is measured by two aspects of the performance: i) the complexity of a movement pattern, and ii) the precision with which it can be repeated. To clarify, we let the complexity of a sequence be given by its entropy.[1]

A. The One-Dimensional Case

For simplicity, we start by treating the one-dimensional case where each movement sequence is characterized by a single measurement per time frame. Let \( x = x_{-1}, \ldots, x_n \) denote a sequence where \( x_t \) gives the value of the measured feature at time \( t \in \{ -1, \ldots, n \} \). We start the sequence from \( x_{-1} \) instead of \( x_1 \) for notational convenience: the first two entries guarantee that an autoregressive model with a look-back (lag) of two steps can be fitted to exactly \( n \) data points. Similarly, we denote by \( y = y_{-1}, \ldots, y_n \) another movement sequence of the same length as \( x \).

We assume that both \( x \) and \( y \) follow a second-order autoregressive model

\[
\begin{align*}
    x_t &= \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \epsilon_t^{(x)}, \\
    y_t &= \eta_0 + \eta_1 y_{t-1} + \eta_2 y_{t-2} + \epsilon_t^{(y)},
\end{align*}
\]

where \( \beta_0, \beta_1, \beta_2 \) and \( \eta_0, \eta_1, \eta_2 \) are real-valued parameters to be tuned using least squares. The second-order model accounts for the basic physical principle that once the movement vector (including direction and velocity) is specified, constant movement contains no information whatsoever.

The errors (or innovations) \( \epsilon_t^{(x)} \) and \( \epsilon_t^{(y)} \) are assumed to be zero mean Gaussian random variables. Since the two sequences are supposed to be repetitions of the same movement pattern, we let \( \epsilon_t^{(x)} \) and \( \epsilon_t^{(y)} \) be correlated with some correlation coefficient \( \rho \in (-1, 1) \). The innovations for different time frames \( t \neq t' \) are assumed to be independent of each other.

Having fitted the parameters to observed sequences, we obtain the residuals

\[
\begin{align*}
    \hat{r}_t^{(x)} &= x_t - \xi_t = x_t - (\hat{\beta}_0 + \hat{\beta}_1 x_{t-1} + \hat{\beta}_2 x_{t-2}), \\
    \hat{r}_t^{(y)} &= y_t - \eta_t = y_t - (\hat{\eta}_0 + \hat{\eta}_1 y_{t-1} + \hat{\eta}_2 y_{t-2}),
\end{align*}
\]

where \( \hat{x}_t \) and \( \hat{y}_t \) denote the predicted values based on the least squares estimates \( \hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2 \) and \( \hat{\eta}_0, \hat{\eta}_1, \hat{\eta}_2 \), respectively.

Under the model (4), the (differential) entropy of each of the sequences can be estimated by plugging the residual variance into the familiar formula for the Gaussian entropy (see [4]):

\[
h(x) \approx \frac{n}{2} \log_2(2\pi e \hat{\sigma}_x^2), \quad h(y) \approx \frac{n}{2} \log_2(2\pi e \hat{\sigma}_y^2),
\]

where \( \hat{\sigma}_x^2 = \frac{1}{n} \sum_{t=1}^{n} (\hat{r}_t^{(x)})^2 \) is the residual variance of \( x \) and \( \hat{\sigma}_y^2 \) is defined similarly.

The mutual information between the movement sequences, which gives the reduction in bits in the entropy of one sequence when we are given the other, is now fully determined by the residuals, and in particular, their correlation \( \rho \):

\[
I(x : y) = -\frac{n}{2} \log_2(1 - \rho^2).
\]

However, since we do not in general know the true correlation coefficient, we need to estimate it from the data. Using the

\[1\] In the case of continuous signals, we continue to do so, keeping in mind the caveats associated with the interpretation of differential entropy, see, e.g. [4] Chapter 8.
empirical correlation coefficient tends to underestimate the true value, and hence, our mutual information estimate based on it will tend to be too high. (For instance, even if the true correlation is zero, we will always get an estimate that is greater than zero.) There are various ways to compensate for this bias. We adopt an approach similar to Rissanen’s classic two-part approximation to the stochastic complexity \([13]\), whereupon the estimated mutual information becomes

\[
\hat{I}(x : y) = -\frac{n}{2} \log_2 \left(1 - \rho^2\right) - \frac{1}{2} \log_2 n,
\]

where the last term will act to overcome the overestimation of the mutual information due to fitting the correlation parameter to a finite amount of data (see, e.g., \([5]\) for many interesting properties of the stochastic complexity formula; those familiar with the concept, may notice that our penalty term is equal to \(\frac{k}{2} \log_2 n\) with \(k = 1\) parameters).

The mutual information has a direct interpretation in terms of the reduction in bits required to encode the sequence \(x\) due to the side information \(y\) being available. Since the mutual information in \(x\) and \(y\) excludes, with high probability, most of the uncontrolled movements and inaccuracies which tend not to be repeated when the movement is performed twice, we argue that it provides a measure of the controlled information in \(x\). To achieve high mutual information, a movement has to be both complex and accurately controlled so that it can be repeated with high precision.

Finally, we define the observed throughput in a sequence \(x\) conditioned on sequence \(y\) as the estimated mutual information per second:

\[
TP(x \mid y) = \frac{\hat{I}(x : y)}{n} = -\frac{R}{2} \log_2 \left(1 - \rho^2\right) - \frac{R}{2n} \log_2 n,
\]

where \(R\) denotes the frame rate (frames per second).

### B. The Multidimensional Case

When handling \(p\)-dimensional sequences, \(p > 1\), where each time frame \(x_t\) is composed of \(p\) measured components (features), \(x_t = (x^{(1)}_{t}, \ldots, x^{(p)}_{t})\), it is not sufficient to simply sum up the information throughput in each of the components separately. This would namely exaggerate the throughput as redundant information that is contained in more than one component was counted several times.

To reduce the effect of redundant information shared between features, we decorrelate the features. To this end, we first perform principal component analysis (PCA) on movement sequence \(x\). We then transform both sequences to obtain two new time series, \(x'\) and \(y'\) where each frame in each sequence is obtained by a linear transformation (the same one for both \(x\) and \(y\)) of the corresponding frame in the original sequence. Typically most of the variance in the new sequences is focused on a fraction of the principal components, and we retain only as many as are required to cover 90 percent of the variance (of \(x\)). The newly obtained lower-dimensional sequences are then analysed using the technique described above, and the throughputs are summed up.

### III. DATA AND PREPROCESSING

In order to study unconstrained performances without limiting ourselves to specific tasks or parts of the body, we analyse motion capture data. Motion capture data is typically obtained by recording a subject by a set of cameras, and using special-purpose image processing technologies to convert the recorded video into variables such as 3D coordinates or angles of joints (wrists, elbows, shoulders, waist, knees, etc).

For out experiment, we recorded the performance of a professional dancer performing movement sequences of her own choice. The recording and motion capture analysis was performed at the Perception, Action and Cognition Lab, University of Glasgow, see Table I and Fig. I. The sequences are recorded at frame rate 120 per second. For each frame, the data contains \(p = 111\) features, corresponding to the three-dimensional coordinates of 37 markers attached to different parts of the body.

The inherent problem in predicting one motion sequence by another is the possible misalignment of the sequences in time. Usually, even very carefully repeated movements are slightly out of synchronization, and hence when predicting the \(t'\) frame of sequence \(x\), the most useful frame of sequence \(y\) may not be the \(t'\) frame but the \(t + \delta\)'th one with \(\delta \neq 0\). Therefore, it is necessary to align the two sequences to obtain a better synchronization.

We aligned each pair of sequences in the data set by applying Canonical Time Warping (CTW)\(^2\)\([18]\), a state-of-the-art technique for aligning sequences describing human behavior. CTW uses the more traditional Dynamic Time Warping (DTW)\([11]\) as an initial solution but improves it by adopting features from Canonical Correlation Analysis (CCA) (see\([2]\)). This allows alignment based on a more flexible concept of similarity than usually used in DTW.

The result of a pairwise alignment of two sequences, with possibly different lengths, is a new pair of aligned sequences whose lengths are equal, such that each frame in one sequence

\(^2\)Matlab code is available at [www.humansensing.cs.cmu.edu/projects/ctwCode.html](http://www.humansensing.cs.cmu.edu/projects/ctwCode.html)

| # | Label                                                                 | \(n\) |
|---|----------------------------------------------------------------------|------|
| 1 | adagio (temps lié, arabesque, pas de bourrée, balancé)                | 4254 |
| 2 | —ii—                                                                  | 4459 |
| 3 | tombé passé de bourrée, Italian fouetté, piqué turn, jeté en tournant| 4001 |
| 4 | —ii—                                                                  | 3724 |
| 5 | petit jeté (glissade jeté, ballotté, balton, entrechat, assemblé)     | 1535 |
| 6 | —ii—                                                                  | 1574 |
| 7 | grand jeté (battement développé, chassé, grande jeté développé, arabesque, fouetté sauté, jeté en tournant) | 1560 |
| 8 | —ii—                                                                  | 1621 |
| 9 | petit jeté (tendu croisé, sissonne devant fermée, derrière fermée, sissonne ouvert pas de bourrée) | 1091 |
| 10| —ii—                                                                  | 1114 |
matches as well as possible with the same movement (similar measured features) in the other. To achieve this, the CTW algorithm duplicates some of the frames in each sequence so as to “slow down” the sequence in question at suitable points; see the example in Fig. 1. When measuring the throughput, we skip the duplicated frames in sequence \( x \) in order to avoid unnecessarily magnifying their impact. Hence, if frame \( t \) is duplicated in sequence \( x \) so that in the aligned sequence, \( x' \), frames \( t \) and \( t + 1 \) are identical, we skip the \( t + 1 \)th frame (of both \( x' \) and \( y' \)) when evaluating the throughput, Eq. (10). The sequences were also normalized so that each feature has mean zero and unit variance. It is important to also note that we compute the residuals of both sequences from the unaligned sequences where there are no duplicate frames. However, the alignment is done based on the actual sequences (not the residuals).

As an undesirable consequence of the use of alignment methods in preprocessing the motion capture data, we lose the information about the temporal accuracy of the movements. Clearly, a significant amount of controlled information are required for timing the motor responses. Working with aligned sequences, there is no way to measure the accuracy to which the repeated performance is synchronized with the original performance. One possibility is to examine the alignment itself to see how much information is required to bring the two sequences in close agreement, and to add this information to the information content due to spatial accuracy. We will explore this issue in further work.

IV. RESULTS AND DISCUSSION

Table II lists all the throughput values for each pair of movement sequences corresponding to the same movement pattern, see Table I. Of all the pairwise throughput values, \( TP(x \mid y) \), the highest one, 1653 bits per second (bps), is obtained for sequence 8 conditioned on sequence 7, see Fig. 1. Their similarity is easily confirmed visually from the video recordings and the animated reconstructions available (not shown). The values are nearly symmetric: the throughput in sequence 7 conditioned on sequence 8 is 1580 bps. The lowest throughput, 640 bps, was observed for sequence 1 conditioned on sequence 2.

As a sanity check, we also evaluated the throughput for pairs of sequences that were not repetitions of the same movement pattern. As expected, the obtained throughput values are all very small or even negative.

In terms of the Minimum Description Length (MDL) Principle \[5\], \[13\], this would be taken to indicate that a model where \( x \) and \( y \) are independent is superior to the model where they are correlated via the innovation sequences. Note that this is equivalent to model selection using the Bayesian Information Criterion (BIC) \[14\].

3Negative values are possible due to the second term, \( \frac{1}{2} \log_2 n \), in Eq. (9).
TABLE II
MEASURED THROUGHPUT VALUES FOR THE SEQUENCES LISTED IN TABLE I

| x   | y   | TP(x | y) |
|-----|-----|------|
| 1   | 2   | 640  bps |
| 2   | 1   | 688  bps |
| 3   | 4   | 1408 bps |
| 4   | 3   | 1481 bps |
| 5   | 6   | 931  bps |
| 6   | 5   | 914  bps |
| 7   | 8   | 1580 bps |
| 8   | 7   | 1653 bps |
| 11  | 12  | 763  bps |
| 12  | 11  | 756  bps |

V. CONCLUSIONS AND FUTURE WORK

The experiment we have described demonstrates the main idea in our framework, i.e., extending the prevailing information-theoretic framework to allow completely unconstrained movements, and thereby, to determine the maximum of the achievable information capacity. Motion capture data provides the best way to characterize such movements in a way that does not rule out any potentially informative aspects in them.

That said, it will be interesting to compare the capacity estimates obtained by other methods, such as pointing devices (the traditional tool in Fitts’ paradigm), data gloves, etc., and to see if the earlier results are replicated. For instance, it is interesting to see if more information can be extracted from Fitts’ original reciprocal pointing task by recording the movements by a data glove or motion capture: the question is whether the path along which the hand operating the pointer moves between the two targets carries additional information beyond the information provided by the end-points, and if it does, how much.

Achieving the goal of constructing a complete and reliable measure of information capacity will lead to a wealth of useful knowledge about the human motor system. Concrete utility is to be seen, for instance, in the study of novel human-computer interfaces that involve free whole-body expression. Possible applications in sports science include training of complex motor schemas with reference models. Potential new diagnostic tools based on monitoring changes in the information capacity of the motor system may offer great societal value through early identification of neurological disorders related to motor dysfunction and in monitoring recovery of neuroplasticity after lesions. We will explore these lines of research in further work.

ACKNOWLEDGMENTS

The authors Frank Pollick for the chance to use the motion capture system at the University of Glasgow, and Naree Kim for dancing. We also thank Kristian Lukander for several discussions on the measurement of information capacity, and Daniel Schmidt and Petri Lievonen for useful comments on an earlier draft of the paper. Any remaining errors are naturally due to the authors. The research by TR, LL, and AM was funded by the Academy of Finland under projects PRIME and MODEST, and the Pascal Network-of-Excellence. The research by AO was funded by Emil Aaltonen Foundation, the Smart Spaces Thematic Action Line of EIT ICT Labs, and the Max Planck Center for Visual Computing and Communication (MPC-VCC).

REFERENCES

[1] J. Accott and S. Zhai. “Performance evaluation of input devices in trajectory-based tasks: an application of the steering law”, Proc. CHI’07, ACM Press, pp. 466–472, 1999.
[2] T. W. Anderson. An Introduction to Multivariate Statistical Analysis, Wiley, 2003.
[3] P. Atkinson. “The best laid plans of mice and men: the computer mouse in the history of computing”, Design Issues 23:46–61, 2007.
[4] T. Cover and I. Thomas. Elements of Information Theory, 2nd Ed., Wiley, 2006.
[5] P. Grünwald. The Minimum Description Length Principle, MIT Press, 2007.
[6] P. M. Fitts. “The information capacity of the human motor system in controlling the amplitude of movement”, J Experim Psychology 47:381–391, 1954.
[7] P. M. Fitts and J. R. Peterson. “Information capacity of discrete motor responses”, J Experim Psychology 67:103-112, 1964.
[8] L. A. Jones and S. J. Lederman. Human Hand Functioning, Oxford University Press, 2006.
[9] I. S. MacKenzie. “A note on the information-theoretic basis for Fitts’ law”, J Motor Behavior 21:323-330, 1989.
[10] I. S. MacKenzie. “Fitts’ law as a research and design tool in human-computer interaction”, Human-Computer Interaction 7:91-139, 1992.
[11] L. Rabiner and B.-H. Juang. Fundamentals of Speech Recognition, Prentice Hall, 1993.
[12] G. H. Robinson and R. C. Kavinsky, “On Fitts’ law with two-handed movement”, IEEE Trans Syst, Man & Cybern, 6:504–505, 1976.
[13] J. Rissanen. “Modeling by shortest data description”, Automatica 14:445–471, 1978.
[14] G. Schwarz. “Estimating the dimension of a model,” Annals of Statistics 6:461–464, 1978.
[15] R. W. Soukoreff and I. S. MacKenzie. “Towards a standard for pointing device evaluation, perspectives on 27 years of Fitts’ law research in HCT”, Int J Human-Computer Studies 61:751–789, 2004.
[16] A. T. Welford. Fundamentals of Skill, Methuen, 1968.
[17] S. Zhai. “On the validity of throughput as a characteristic of computer input,” IBM Research Report RJ 10253, IBM Research Center, Almaden, California, 2002.
[18] F. Zhou and F. de la Torre. “Canonical time warping for alignment of human behavior”, Advances in Neural Information Processing Systems (NIPS), 2009.