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Support vector machines categorize the scaling of human grip configurations

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In previous work (Cesari & Newell, 2002), we used a graphical dimensional analysis to show that grip transitions obey the body-scaled relation $K = \ln L_o + \ln M_o/(a + bM_h + cL_h)$, where L_o and M_o are the object's length and mass, and L_h and M_h the length and mass of the grasper's hand. However, the generality of the equation was limited by the ad hoc graphical method that defined the lines for grip separation and by the assumption that these lines be negatively sloped and parallel to one another. This article reports an independent test of this relation by the geometrical *and* statistical categorization of body-scaled invariants for the transition of human grip configurations through support vector machines (SVMs). The SVM analysis confirmed the fit of linear, negatively sloped, and approximately parallel transition boundaries in the scaling of human grip configuration within a single hand. The SVM analysis has provided a theoretical refinement to the scaling model of human grip configurations.

Transitions in the grip configurations used to grasp objects scaled in mass, size, and density have been recently studied by Cesari and Newell (1999, 2000a, 2000b, 2002), who proposed that grip configurations are categorized on the basis of the dimensional scaling factor K, expressed by the relation:

$$K = \ln L_o + \frac{\ln M_o}{a + bM_h + cL_h}, \qquad (1)$$

where L_o and M_o are the length of the side (or diameter) and the mass of the grasped object (cubes or spheres), and L_h and M_h are anthropometric measures of length and mass of the grasping hand. This body-scaled relation was shown to be invariant across young children and adults, and to effectively accommodate the high level of biomechanical redundancy and individual differences in the prehensile act of displacing an object. Notwithstanding the robustness shown by Equation 1 across different experiments (see also Choi & Mark, 2004, on human reach actions), its scope was somewhat limited by the ad hoc, visually based body-scaling methods we employed in our previous analyses. The scaling factor was defined graphically by drawing the most "obligatory" line (see below) to divide the different grip configurations based on the object dimensions. Transition boundaries in the mass versus length object space were then assumed to be linear and parallel to this line, with negative slopes.

To examine the validity of these assumptions, we report here the results of a *support vector machine* (SVM; Shawe-Taylor & Cristianini, 2004) analysis on our previously collected grip transition data (Cesari & Newell, 2002). The SVM allowed us to characterize the geometrical *and* statistical regularities of grip transitions in a principled and non–ad hoc fashion. It will be shown that the SVM analysis confirmed the good fit of linear, negatively sloped, and approximately parallel transition boundaries for the grip transitions within one hand but not for the transition from one to two hands. This provides strong support for the relation set forth in our previous work (Equation 1), while defining a natural domain for its applicability to grip transitions within one hand.

Dimensional Analysis of Grip Configurations

The core idea underlying this and prior work is that people grasp objects of different dimensions using different grip configurations, but do so in a highly orderly fashion in spite of the large number of degrees of freedom of the hand and the arm complex (Kapandji, 1970; Malek, 1981; Newell & Cesari, 1998). A grip configuration is defined in terms of the number of digits in contact with the object during its transport from one place to another (Cesari & Newell, 2002; Newell, Scully, McDonald, & Baillargeon, 1989). This definition gives rise to five primary grip configurations characterized by a natural ordering, namely: two-, three-, four-, and five-digit grips, plus a two-hand grip. Our hypotheses were twofold. First, we conjectured that subjects would systematically add one digit contact with the object at a time, as the dimension of the object increased. Second, we conjectured the existence of an invariant scaling factor regulating these different grip configuration modes, independent of object size and mass.

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In order to investigate these hypotheses, we recruited subjects so as to cover a large range of body sizes (the body mass of the subjects ranged between 46 and 79.2 kg, and the height ranged between 154.9 and 190.5 cm). For each subject, we collected standard anthropometric measures of hand size (Snyder et al., 1977): The hand length used for the scaling analysis was the length measured from the wrist crease to the tip of the middle finger of the extended hand. The relative mass of the hand was estimated from the mass–inertial characteristics of human body segments based on radioisotopic methods (Zatsiorsky, Seluyanov, & Chugunova, 1990). On our subjects, hand length ranged from 16.5 to 20 cm and hand mass from 0.29 to 0.57 kg. In the experiment, we also used different sphere sizes for each of five material densities (see Figure 1A: balsa, pine, purpleheart, aluminum, steel), with uniform density throughout the volume of each object. Figure 1B shows the size and mass of the objects used in the experiment on a logarithmic scale. Each subject completed a series of trials in which a sphere resting on a table was grasped and displaced from its initial position to a new final position.

We started by analyzing the data with the ad hoc, visually based approach used in our previous work (Cesari & Newell, 1999, 2000a, 2002). We marked the preferred grip used for each sphere by each subject on a plot of object mass versus object length (both on natural log scale). This determined a "map" of the number of digits used by each subject across 63 spheres. An instance of such a map for 1 subject is shown in the upper right graph of Figure 1.

Second, we determined graphically the linear transition boundaries that best separated contiguous grip configurations, with the assumption that all such boundaries be parallel and of negative slope. As in our previous studies, we found that the common slope of these transition lines could be easily identified because, for at least one of the transitions, the data constrain the slope quite stringently; we call the line for this transition most "obligatory." For instance, the most obligatory transition line for the subject whose map is represented in Figure 1B is the one that divides the four- and five-digit grips. We indicate with $-\beta$ the negative slope of the most obligatory line, and we can write equations for our parallel linear boundaries as

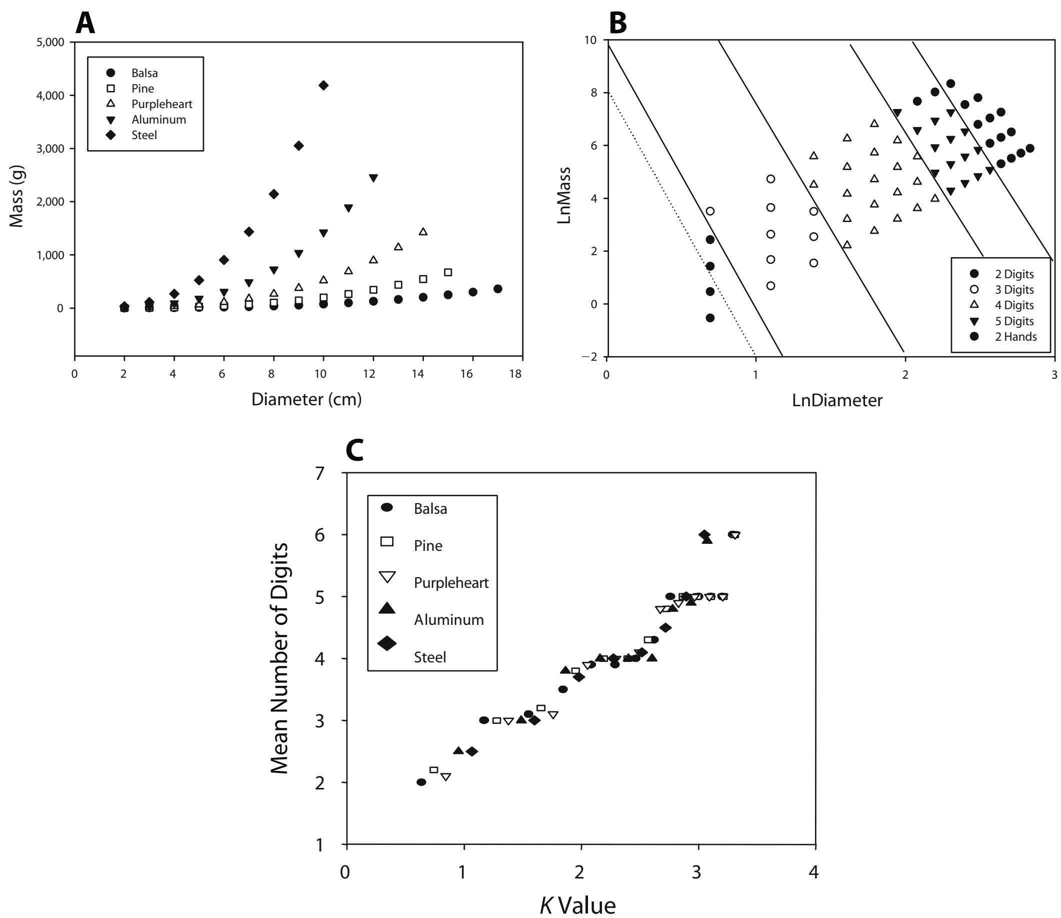

Figure 1. (A) A plot of the mass of each sphere versus its diameter length—all densities are represented. (B) Best-fitting separating lines derived by graphical dimensional analysis for a single subject. These lines are assumed to have the same slope. On the axes are logarithm of mass (LnMass) and logarithm of diameter (LnDiameter) of the grasped spheres. (C) Grip configuration (mean number of digits) versus the *K* value (from Equation 5) for the same subject.

$$\ln M_s = \alpha_j - \beta \ln L_s, \tag{2}$$

where M_s and L_s are mass and diameter of the sphere, and α_j is the intercept characterizing the jth transition. Dividing the left- and right-hand side of Equation 2 by the common slope $-\beta$, we obtain

$$\alpha_j/\beta = (-\ln M_s/{-\beta}) - (\beta \ln L_s/{-\beta}). \tag{3}$$

Renaming $K_j = \alpha_j/\beta$ the transition point values, we therefore have an expression for K as

$$K = \ln L_s + \ln M_s/\beta. \tag{4}$$

This graphical approach confirmed the existence of clear transition lines that categorize the scaling of different grips. To go from Equation 4 to the relation for K in Equation 1, we proceed as in our previous work (Cesari & Newell, 1999, 2000a, 2002). The $-\beta$ of the most obligatory line ranged between −6 and −9 across the 10 subjects in our study. We regressed the individual slopes on individual hand anthropometric measures (Zatsiorsky et al., 1990), fitting the equation

$$\beta = a + b\,M_h + c\,L_h + \text{error},$$

where M_h and L_h are hand mass (in kg) and length (in cm). This fit had an excellent coefficient of determination ($R^2 = .95$), and allowed us to estimate the body coefficients a, b, and c in the denominator of Equation 1. Based on these estimates, the equation becomes

$$K = \ln L_s + \frac{\ln M_s}{2.73 + 13.7M_h - 0.056L_h}. \tag{5}$$

For each subject, we can then plot K (Equation 5) versus the mean number of digits used. The bottom graph of Figure 1 shows an instance of such a plot for 1 subject and allows us to appreciate how well the variable K organizes the grip pattern.

The next task is to test the statistical significance of K in scaling grip configurations. First, for each subject, we need to define points of switch (grip transition) in terms of Equation 5. For example, to define the point of switch from two to three digits for a given subject, we use the mass and length of the largest sphere (e.g., in terms of K value) grasped with two digits and the smallest sphere (again in terms of K) grasped with three digits to compute two values of K according to Equation 5, and then average them. The same is done for each grip transition, and for each subject.

The points of switch were practically the same for all subjects, notwithstanding the variability in body size. Analyzing the K values for each transition point as a function of the switch patterns, we find significant evidence of a main effect [$F(3,36) = 201.8$, $p < .001$]. The transition from two to three fingers is predicted at K (Equation 2) equals 1.2—that is, below 1.2, the grip configurations for all subjects are predicted to consist of two digits, whereas above this value, the grip configurations are predicted to consist of three digits. In the same way, the switch from three digits to four digits is predicted at $K = 2$, from four digits to five digits at $K = 2.8$, and from five digits to two hands at $K = 3.3$. When comparing switches across our previous three studies (Cesari & Newell, 1999, 2000a, 2002), we find no statistical difference between the K estimates for changes in grip configuration.

SVM Analysis of Grip Configurations

Equation 1, and its estimated version Equation 5, were derived with an ad hoc, visually based procedure that postulates linear, negatively sloped, and parallel transition boundaries between grip configurations. To go beyond this approach, and verify the accuracy of its assumptions and findings, we submit our data to an SVM analysis. SVM is a machine learning tool developed at the end of the 1970s (Vapnik, 1979) that has found widespread application in classification and pattern recognition problems: among many examples are face recognition (Gong, McKenna, & Psarrou, 2000) and gait pattern recognition (Begg & Kamruzzaman, 2005; Begg, Palaniswami, & Owen, 2005).

In a binary classification problem, the main aim is to allocate observations (i) to one of two classes, based on the values assumed by a feature vector, say $x_i \in \mathbf{R}^k$. A training set—that is, a collection of observations (x_i, y_i) for which the class labels y_i are known—is used to define a classification boundary separating the two classes in the feature space. As a convention, the labels can be coded as $y_i = \{-1, +1\}$. The simplest instantiation of SVM (linear kernel SVM) produces a linear classification boundary by estimating the (shifted) hyperplane of $\mathbf{R}^k$ that gives the best separation between observations belonging to the two classes. Loosely speaking, the algorithm attempts to identify a $w \in \mathbf{R}^k$ and a $u \in \mathbf{R}$, such that

$$x_i^w + u \geq +1, \text{ for } y_i = (+1) \tag{6}$$

$$x_i^w + u \leq -1, \text{ for } y_i = (-1). \tag{7}$$

Even when perfect linear separation is not possible, the algorithm will seek parameter values that maximize the separation, identifying the plane at maximal distance from the data points that do satisfy Equations 6 and 7. On a technical note, the SVM algorithm contains internal parameters (a regularization parameter in the linear kernel case, and an additional bandwidth parameter in the nonlinear RBF kernel case discussed below) that need to be "tuned" prior to running the algorithm (Suykens, Van Gestel, De Brabanter, De Moor, & Vandewalle, 2002).

We did so by performing a grid search on the space of these parameters, and selecting the values that led to best SVM performance. Performance was measured as the area under a receiver operating characteristic (ROC) curve obtained from cross-validation, which summarizes the sensitivity versus specificity trade-off in classification.

Once the SVM algorithm is run with optimal internal parameters, and the parameters w and u are produced as output, any point x in the feature space can be classified as belonging to class 1 (label +1) or class 2 (label −1) with the simple rule

$$\text{if } \operatorname{sgn}(x^w + u) = +1 \text{ then } x \in \mathbf{C}_1;$$
$$\text{if } \operatorname{sgn}(x^w + u) = -1 \text{ then } x \in \mathbf{C}_2,$$

where sgn is the sign function.

SVM can also be used for classification problems involving more than two classes, performing a collection of binary classifications—for example, classifications between pairs of classes ("one against one"), or between each class and the rest of the data ("one against all"). Moreover, SVM can be used to identify nonlinear classification boundaries, employing nonlinear kernel equations, such as polynomial, radial basis function (RBF), and sigmoid function kernels.

Here, we apply SVM with both linear and nonlinear (RBF) kernels to the grasping data analyzed in the previous section and in Cesari and Newell (2002). The feature space for our classification is $\mathbf{R}^2$, with feature vectors comprising $x_1 = \ln L_s$, $x_2 = \ln M_s$. The aim is to evaluate the fit provided by linear transition boundaries in comparison with that provided by nonlinear boundaries, as well as the parallelism of linear boundaries. For these data, the "one against one" approach is reasonable in terms of class sizes, since the number of data points available for each class (grip configuration) is comparable. Moreover, we can restrict attention to pairs of classes that are naturally contiguous in terms of the grip configuration order (from two to three digits, from three to four, and so on). Thus, we compute linear and nonlinear SVM boundaries for each of four binary classifications between the five contiguous grip configurations (two vs. three digits, three vs. four digits, four vs. five digits, and five digits vs. two hands).

Linear SVM produces four separating lines, with estimated slopes and intercepts, say $\beta_j = -w_{1,j}/w_{2,j}$ and $\alpha_j = -u_j/w_{2,j}$, $j = 1, 2, 3, 4$, for every subject in our study (note that here, the four slopes are *not* required to coincide). Correspondingly, we compute four points of switch $K_j = \alpha_j/\beta_j$ for each subject. Nonlinear (RBF) SVM produces four separating curves for every subject. The quality (goodness of fit) for each linear and nonlinear classification is measured by the percentage of misclassified points in cross-validation—the smaller the percentage, the better the classification.

Results

The classification performance afforded by linear boundaries on our data was very good. On average, over the binary classifications and the subjects, the misclassification rate was 10.5%, with a standard deviation of 3%. In comparison, RBF nonlinear boundaries increased the average misclassification rate by 1.5% (to 12.1%), as well as its variability across binary classifications and subjects (the standard deviation reached 7.5%). This result constitutes strong and principled evidence for the use of linear transition boundaries between grip configurations.

Figure 2 (upper graph) shows the ln diameter versus ln mass plane for the same subject used in Figure 1, but with linear boundaries obtained through SVM: The numbers on the plot represent slopes for each grip transition (to be taken in negative value). Table 1 gives values of the SVM slopes for the four transitions and the 10 subjects in the study. Although slopes for all transitions and for all subjects are negative, the picture emerging for various switches is different.

Most important here are the slopes characterizing the three- to four- and the four- to five-digit transitions. In our previous dimensional analysis, we found these to be the most "stable" transitions; that is, the ones that corresponded to subjects' most "obligatory" lines. Moreover, we found that the (common) slope for each subject was related to his/her hand size. Indeed, SVM slopes for the three- to four- and four- to five-digit transitions are similar to one another for each subject, and differ substantially across subjects, seemingly as a function of the subjects' hand size (the bigger the hand, the larger the negative slope value—see Table 1). SVM slopes for the two- to three-digit transition, which are somewhat lower, and identical across subjects, can be interpreted as an artifact of our experimental design. (This switch corresponds to a large gap in mass vs. length on the log–log scale, which renders separating slopes ill-determined; see Discussion.)

For the switch between five digits of one hand and two hands, SVM slopes have consistently smaller negative values in comparison with the other switches, contradicting parallelism. However, one can argue that a five-digit grip and a two-hand grip represent patterns so unlike one another that a different object mass–length relationship is necessary to describe the transition between them. In particular, when transitioning from one to two hands, the mass of the object acquires a bigger effect relative to the diameter. Also here, slopes appear related to the subjects' hand size, with evidence of an even stronger mass effect for small subjects.

To test these observations, we ran a repeated measures ANOVA considering as factors the SVM grip separation slopes, and "small" versus "large" subjects (we divided subjects in two groups of 5 each, based on hand size). We omitted the two to three digits from this analysis for the reasons mentioned above. The ANOVA was significant [$F(1,8) = 128.3$, $p < .001$] and the effect for slopes was significant [$F(2,16) = 183.6$, $p < .001$], showing that subjects with bigger hands had significantly steeper slopes than did subjects with smaller hands (see Table 1). The Tukey's post hoc test provided evidence that there was no difference between the three- to four- and four- to five-digit slopes, whereas both were different from the five-digit to two-hand slope. In order to test the scaling factors defined by the ratios $K_j = \alpha_j/\beta_j$, we again ran a repeated measures ANOVA, this time having as factors the K values for all the grip transitions and the two size groups, as defined previously. Here, the between-subjects analysis was nonsignificant, showing that there were no sizeable differences between small and big individuals. However, we found a significant effect for K [$F(3,24) = 333.23$, $p < .001$]. Thus, K values separate the

Table 1
SVM Slopes for the Four Grip Transitions and Body Parameters

Subjects	2d–3d	3d–4d	4d–5d	5d–2h	Hand Mass	Hand Length
1	−6.9	−10.9	−10.8	−4.6	0.6	20.0
2	−6.9	−11.0	−13.1	−3.8	0.5	19.3
3	−6.9	−12.5	−13.1	−4.1	0.4	18.5
4	−6.9	−10.4	−9.8	−4.9	0.5	18.1
5	−6.9	−11.7	−12.0	−4.7	0.4	17.5
6	−6.9	−7.4	−7.0	−2.5	0.3	17.2
7	−6.9	−7.5	−6.0	−2.2	0.3	17.0
8	−6.9	−7.5	−6.0	−2.3	0.3	16.5
9	−6.9	−7.2	−7.4	−3.3	0.3	16.5
10	−6.9	−7.2	−7.9	−2.8	0.3	16.5

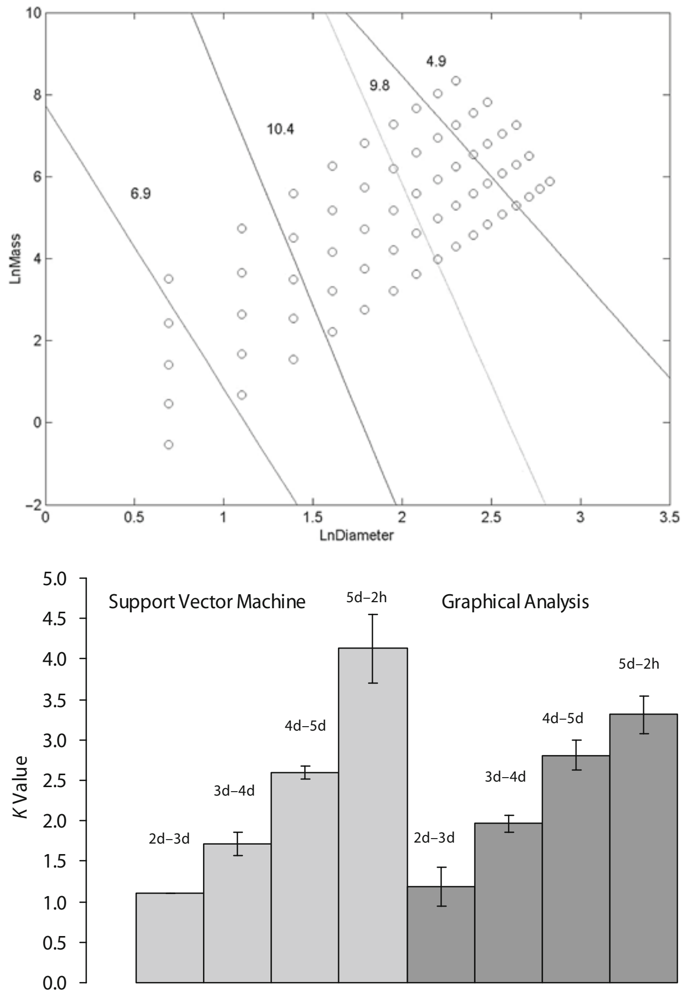

Figure 2. Top: Best-fitting separating lines derived by support vector machines for the same subject as in Figure 1. Slopes are allowed to vary across lines. On the axes are logarithm of mass (LnMass) and logarithm of diameter (LnDiameter) of the grasped spheres. Slopes (to be taken in negative value) are reported on the plot. Bottom: Histogram showing the *K* values calculated by using the two analyses: graphical dimension analysis and support vector machines.

grip configurations, but there is no significant difference for grip transitions between subjects with bigger hands and subjects with smaller hands.

Table 2 and the histogram on the bottom of Figure 2 show switch points (i.e., the *K* values) for the four transitions and the 10 subjects in the study, calculated via SVM and via graphical dimensional analysis (DA).

Discussion

In this article, we have applied SVMs to the data on grasping previously analyzed in Cesari and Newell (2002). We sought to provide more formal evidence for the body-scaling Equation 1, and to test the linearity and parallelism assumptions imposed by our previous DA for the definition of grip transitions. We were able to show that *K* defined in Equation 1 is an effective scaling parameter for defining switches among different grip configurations, and that assuming linear separating boundaries with a common negative slope is a good approximation for grip transitions within one hand.

Our previous graphical DA employed several ad hoc steps to capture the dimensionless object/body ratio that scales the grip configurations for each individual. Here, by using SVMs with a linear kernel, we estimated linear boundaries that optimize the separation between contiguous grip configurations, allowing these boundaries to have different slopes: The corresponding *K* values are defined as the ratios between each pair of estimated slope and intercept. We also estimated nonlinear boundaries using SVMs with an RBF kernel (Shawe-Taylor & Cristianini, 2004; Vapnik, 1979).

The SVM analysis showed that nonlinear boundaries do not improve classification performance, which is evidence for the adequacy of linear transition loci. Concern-

Table 2
***K* Value (Ratios Slope/Intercept) for the Four Transitions for SVM and Graphical Dimensional Analysis**

Subjects	2d–3d SVM	3d–4d SVM	4d–5d SVM	5d–2h SVM	2d–3d DA	3d–4d DA	4d–5d DA
1	1.1	1.6	2.7	3.9	1.6	2.2	2.9
2	1.1	1.6	2.7	3.4	1.0	1.8	2.7
3	1.1	1.9	2.5	4.2	1.2	2.0	2.9
4	1.1	1.8	2.5	4.0	1.6	2.0	3.2
5	1.1	1.8	2.6	3.7	0.9	1.9	2.7
6	1.1	1.8	2.6	4.4	1.1	1.9	3.1
7	1.1	1.8	2.6	4.7	1.2	1.9	2.6
8	1.1	1.5	2.5	3.9	1.2	2.0	2.7
9	1.1	1.5	2.7	4.4	1.0	1.9	2.8
10	1.1	1.8	2.6	4.7	1.1	1.9	2.8
M	1.1	1.7	2.6	4.1	1.2	2.0	2.8
SD	0.0	0.1	0.1	0.4	0.2	0.1	0.2

ing linear SVM boundaries, we found that the two slopes for the three- to four- and four- to five-digit transitions are indeed similar for each individual, and vary across individuals depending on hand size. These two switches are of particular relevance: They were the ones used to define "most obligatory lines" in our graphical analysis, which also generated slopes depending on the subjects' hand size (the bigger the hand, the larger the negative value of the common slope). Thus, the SVM analysis confirms our graphical DA results relative to these two switches.

The situation is different for the two- to three-digit transition and, more interestingly, for the transition between five digits of one hand and two hands. SVM slopes for the two- to three-digit switch are somewhat lower than the ones associated with the three- to four-digit and four- to five-digit transitions, and show no variation across subjects with very different hand sizes. There is a simple explanation for this based on our experimental design: In the log–log plot of sphere mass versus sphere diameter, the gap between smallest spheres and next bigger spheres at the two- to three-digit switch is large enough so as to make separating slopes essentially ill-determined. Consequently, the two- to three-digit transition was never used to define "most obligatory lines" in our graphical DA, and SVM was able to fit equal slopes across subjects, regardless of their hand size.

Concerning the five digits to two hands switch, SVM slopes for each subject are substantially lower than those associated with switches within the digits of one hand. We interpret this as evidence that the pattern of grasping with two hands is deeply different from the one performed with one hand, relying on different object mass–length proportions. This seems reasonable, given the many differences between adding a digit from one hand to the grip configuration and forming a two-hand grip.

As further evidence for this interpretation, we note the results found in our previous work (Cesari & Newell, 2002), where we also performed DA on the impulses applied to the object. We found that all subjects kept the impulse constant up to the four-digit grip, whereas the five-digit grip was maintained for much higher object dimensions (mass and length). Up to four digits, subjects were adding one digit every time the impulse reached a certain threshold, thus keeping the impulse invariant across grips. Once the grip reached five digits (given the increment of the mass and length of the object), the subjects did not switch to two hands at the same impulse threshold, but maintained the five-digit grip and applied more impulse instead. In other words, the scaling relation for the addition of the second hand was not that used to add a digit within the hand.

SVM gave good classification performances on our grip data. Taking into account the geometrical properties of the hand has shown to be powerful in sequentially discriminating patterns across the grips (i.e., from two to three digits, from three to four, four to five digits, and one hand to two hands; Kapandji, 1970; Newell & Cesari, 1998). Studies on the structure and function of the human hand and, in particular, of the fingers within one hand, hypothesized the idea of "positioning for grip" based on the architectural relationship between length and mobility of the thumb with respect to length and mobility of the rest of the fingers (Malek, 1981). Kapandji (1970) recognized that there is a relationship between strength, number of digits, and volume of the object grasped. Even if he never formalized this relationship in terms of dimensional formulae, his thought can be interpreted as a proportionality relationship [V ∝ R ∝ number of fingers] linking the object volume (V), reactive forces (R), and the number of fingers. The general idea is that in order for an object of a given weight to be successfully held in the hand, it is necessary that the digits express equal and opposing reactive forces, and the total reactive forces and moments between the object and the hand sum to zero [$\Sigma F = 0$; $\Sigma M = 0$]. In our work, we found that these intuitions can be quantified by applying a linear scaling relationship that considers the number of digits involved on the basis of the relation among object and hand masses and sizes.

Our original Equation 1 allowed us to predict grip configuration on the basis of a small number of parameters—namely, the size and mass of the object and of the grasping hand. Similarly, once an SVM classifier is trained on data pertaining to 1 subject, it allows us to predict grip configuration (y) for any new data point in the feature space (x; object size and mass—see Equations 6 and 7). In other words, SVM can be trained to produce grasping predictions for any subject and object dimensions, and affords a very general categorization of grip configurations over a wide range of scaling conditions. As a supervised classification algorithm, SVM "learns" from the training data effective separating boundaries in the feature space, so that the class of a new data point can be predicted on the basis of its position (i.e., the grip configuration employed by a given subject to grasp a new object can be predicted on the basis of the object mass and length).

In summary, SVM algorithms have demonstrated considerable power to discriminate important properties in the transitions of grip configurations. These algorithms are likely to have a range of fruitful applications to classification problems in psychology. SVM algorithms have already been applied to subtle and difficult classification problems, such as facial recognition (Gong et al., 2000), and offer options beyond the ones illustrated in this article. For instance, SVM fits can be sequentially updated to refine discrimination in situations in which the amount of available data increases over time. Also, although nonlinear kernels did not improve classification performance for the grip data considered in this article, they may be critical for accurate classification in other psychological phenomena.

AUTHOR NOTE

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