A Computational Estimate of the Physical Effort in Human Poses

Yinpeng Chen, Hari Sundaram, Jodi James

Arts, Media and Engineering Program, Arizona State University, Tempe, AZ, 85281
{yinpeng.chen, hari.sundaram, jodi.james}@asu.edu

Abstract. This paper deals with the problem of estimating the effort required to maintain a static pose by human beings. The problem is important in developing dance summarization and rehabilitation applications. We estimate the human pose effort using two kinds of body constraints – skeletal constraints and gravitational constraints. The extracted features are combined together using SVM regression to estimate the pose effort. We tested our algorithm on 55 dance poses with different annotated efforts with excellent results. Our user studies additionally validate our approach.

1 Instruction

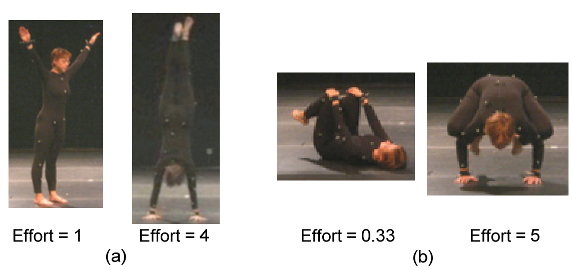

Figure 1. Two pose pairs with similar appearance and different physical effort.

This paper deals with the problem of estimating physical effort for a static human pose using SVM regression. The problem is important in both effective pose classification and dance summarization applications. Human beings routinely are able to distinguish between *human poses that appear to be very similar* by referring to their own physical experience. For example, both pairs of poses in Figure 1, appear to be very similar (modulo rotation). However it is trivial for human beings to see that the second pose in Figure 1(a)-(b) is very challenging to do for most people. We conjecture that human beings pay *greater attention* to the poses with greater physical effort, as they are reminded of the difficulty of doing the pose. Note also that the *perception* of effort differs from the *subjective experience* of physical effort. Hence it is extremely important to develop ground truth effort estimates using the domain expertise of a trained Laban Movement Analysis expert (one of the authors).

The analysis of physical effort is playing an important role in several emerging multimedia applications – (a) online dance pedagogy and (b) biofeedback for rehabilitation.

online dance pedagogy: With high speed communication networks being available more widely, online dance pedagogy is beginning to complement traditional in-person dance training. Traditional review of dance materials (through video), is linear, and time consuming. Mechanisms that automatically summarize *key movement phrases* and present it in video form would thus be exceedingly useful. Effort based video summarization offers a an effective mechanism to communicate key ideas to the dance students.

biofeedback for rehabilitation: We have been working on developing an experiential media system [2] that integrates task dependent physical therapy and cognitive stimuli within an interactive, multimodal environment. Integrating estimates of physical effort would allow us a much richer understanding of patient rehabilitation.

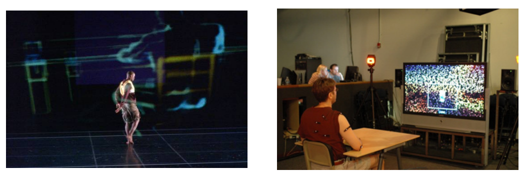

Figure 2. left: multimodal dance, right: multimodal rehabilitation of stroke patients.

Pose classification is a traditional computer vision problem [1,3]. However the focus there is appearance based matching or matching in an object based representational space. However, the classification does *not* take into account the physical experience of doing the pose, thus potentially misclassifying poses with different physical effort that appear to be similar. Other related works [6,8] deal with motion quality modals based on Rudolf Laban's Effort Qualities. In Laban Movement Analysis (LMA), effort encompasses qualities of space, weight, time and flow and represents the expressive quality of style within the dynamics of human movement rather than static human poses.

We propose a human pose effort estimation algorithm based on SVM regression. We first extract two kinds of features related to human pose effort: (a) physical constraints and (b) gravitational constraints. Then we use SVM regression techniques to combine these features together to estimate effort. We tested our algorithm on an annotated dance pose set with excellent results. We additionally validated our results with user studies.

2 Pose Representation by 3D Markers

In this section, we discuss the marker based representation of 3D human pose. Each pose consists of 35 labeled 3D marker coordinates captured from a marker-based motion capture system.

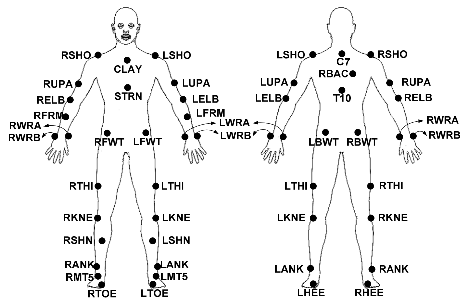

Figure 3. Positions and labels of 35 markers

A calibrated 3D capture system provides labeled data, specifying the location on the body for each marker. Figure 3 shows positions and labels of 35 markers. Let us denote the labeled 3D marker coordinates of a pose as $X_i=(x_i,y_i,z_i)^T$, $i=1,\dots,N$ where N is the number of markers (N=35). In this paper, we also use the marker label as subscript.

3 Features from Physical Constraints

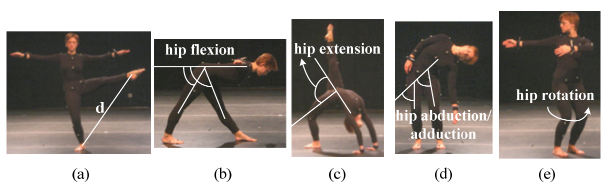

Figure 4. Five physical constraints. (a) foot distance, (b) hip flexion, (c) hip extension, (d) hip abduction/adduction, and (e) hip rotation.

Physical constraints include muscle and skeleton structure which are not related with gravity (e.g. human's torso can not lean backward easily and the two legs can not be split easily). We observe that the physical limitations mainly focus on the joints between limbs. The joint constraint can be represented by the relationship between two connected limbs. We also observe that arm movements in comparison to leg movements have a wider range of motion due to the greater mobility of the shoulder joint. Hence, in this paper, we ignore the physical limitations of shoulder joints and focus on the hip joints. We have used a simple model where the torso and thigh are related through a hip joint.

We use a simple feature, foot distance, to represent inter-leg relationship and four joint angles (1 hip *flexion*, 2 hip *extension*, 3 hip *abduction/adduction* and 4 hip *rotation*) to represent torso-leg relationship. The foot distance and four hip joint angles are shown in Figure 4. Note that we use torso as the reference when we discuss torso-leg relationship.

3.1 Inter-leg constraint

We use foot distance to represent inter-leg constraint. The foot distance can be easily estimated by marker based data. Let us denote the centroid of four markers on the left/right foot as X_{LF}/X_{RF}. The four markers of the left foot are placed on the left ankle (X_{LANK}), left heel (X_{LHEE}), left metatarsal five (X_{LMT5}) and left toe (X_{LTOE}) (see Figure 3). Thus, the normalized foot distance d_F is defined as:

$$d_F = \begin{cases} \dfrac{d(X_{LF}, X_{RF}) - d_{normal}}{d_{\max}} & \text{if } d(X_{LF}, X_{RF}) > d_{normal} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where $d(\cdot)$ is L_2 distance metric, d_{normal} is the foot distance when a person stands naturally, and d_{max} is the maximum possible foot distance for the person which equals the sum of lengths of two legs. If foot distance is less than d_{normal}, there is no inter-leg effort ($d_F=0$). However the overall pose may have other efforts due to other body constraints.

3.2 Torso-leg constraints

There are three degrees of freedom (DOFs) in left/right hip joint – (a) *flexion/extension*, (b) *abduction/adduction* and (c) *rotation*. We use three joint angles to represent these three DOFs. The three joint angles between two limbs can be obtained by using three non-co-linear positioned markers on each limb. We selected three markers (X_{C7}, X_{T10}, X_{RBAC}) on the torso, three markers (X_{LBWT}, X_{LTHI}, X_{LKNE}) on the left thigh and three markers (X_{RBWT}, X_{RTHI}, X_{RKNE}) on the right thigh to compute left/right hip joint angles. The details for computing joint angles are found in [4]. We select natural standing pose as the reference whose left/right hip joint angles are zero.

Let us denote θ_{LEF} and θ_{REF} as the left and right hip *flexion/extension* (ref. Figure 4 (b), (c)). The relationship between torso and left leg (or right leg) is said to be flexion if θ_{LEF} (or θ_{REF}) is positive, else it is extension. Let θ_{LAA} and θ_{RAA} be the left and right hip *abduction/adduction* (ref. Figure 4 (d)). A positive value means abduction and negative value means adduction. Let us denote θ_{LR} and θ_{RR} as the left and right hip rotation (ref. Figure 4 (e)).

The hip flexion and hip extension have to be measured separately because hip flexion require less efforts than the extension due to the presence of pelvis-vertebrate joint. The overall hip flexion θ_F and hip extension θ_E can be computed by:

$$\theta_F = \frac{\theta_{LEF} \cdot u(\theta_{LEF}) + \theta_{REF} \cdot u(\theta_{REF})}{2\pi}, \quad \theta_E = \frac{-\theta_{LEF} \cdot u(-\theta_{LEF}) - \theta_{REF} \cdot u(-\theta_{REF})}{2\pi}, \quad (2)$$

where θ_{LEF} and θ_{REF} are left and right hip flexion/extension angles, $u(\cdot)$ is standard step function.

In contrast to hip flexion and extension, we do not distinguish hip abduction and hip adduction and consider them equivalently. This is because hip extension needs more effort than hip flexion whereas the effort difference between hip abduction and hip adduction is small. Hence, the hip abduction/adduction θ_A is defined as follows:

$$\theta_A = \frac{|\theta_{LAA}| + |\theta_{RAA}|}{2\pi}, \tag{3}$$

where θ_{LAA} and θ_{RAA} are left and right hip abduction/adduction angles.

In similar manner to hip abduction/adduction, we combine the left and right hip rotation together to compute the hip rotation as follows:

$$\theta_R = \frac{|\theta_{LR}| + |\theta_{RR}|}{\pi}, \tag{4}$$

where θ_{LR} and θ_{RR} are left and right hip rotation angles. We consider clockwise and anticlockwise rotations equivalently.

4 Features from Gravitational Constraints

In this section, we shall discuss features from gravitational constraints. Gravitational constraints comprise two factors: *limb torque* and *supporting-limb effort*. *First*, we introduce gravity torque of each limb that is related to the effort of the corresponding joint. For instance, the larger the arm gravity torque, the more effort needed to be put on the shoulder. *Second*, we discuss the effort on supporting limbs. Supporting effort of a limb is inversely proportional to supporting power of the limb. For instance, since the hip and the torso have more supporting power than the legs, a sitting pose needs less supporting effort than a standing pose.

4.1 Limb Gravity Torque

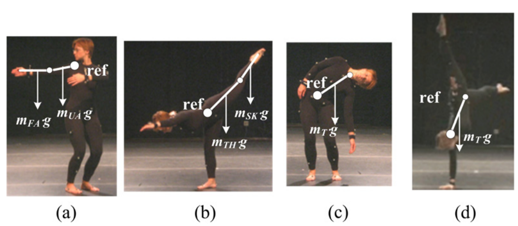

Figure 5. Limb gravity torque. (a) arm torque, (b) leg torque, (c) torso torque with respect to hip, (d) torso torque with respect to shoulder.

In this section, we shall discuss gravity torque computation of three kinds of limbs – *arm*, *leg* and *torso* (see Figure 5). We compute the limb gravity torque only if the limb is *not* the supporting limb. This is because limbs in contact with the ground experience a torque due to the normal reaction. This has an effect of canceling the torque of gravity on the limb. Hence effort to support the limb is reduced. Therefore, to determine the total effort required to counter-balance gravitational torque, we need to first determine supporting limbs.

Determining Supporting Limbs

Since we know the label information of markers (ref. Section 2), we can easily determine which limbs are the supporting limbs and obtain the supporting-limb vector. We first classify 35 markers into 10 groups – (1) left hand, (2) right hand, (3) left arm, (4) right arm, (5) left foot, (6) right foot, (7) left leg, (8) right leg, (9) torso and (10) hip. Then, we construct the supporting-limb vector:

$$f_{sf} = [s_{LH}, s_{RH}, s_{LA}, s_{RA}, s_{LF}, s_{RF}, s_{LL}, s_{RL}, s_T, s_H]^T \ , \tag{5}$$

where s_{LH}, s_{RH}, s_{LA}, s_{RA}, s_{LF}, s_{RF}, s_{LL}, s_{RL}, s_T and s_H, are supporting indicator of left hand, right hand, left arm, right arm, left foot, right foot, left leg, right leg, torso and hip respectively. If any element of f_{sf} is positive, it implies that the corresponding limb is the supporting limb and zero implies a non-supporting limb. Computing this vector is a straightforward procedure based on the relationship of the markers to the ground. Each indicator except left and right foot (s_{LF}, s_{RF}) equals 1 if at least one marker on the corresponding limb is close to the ground (Z coordinate is less than threshold ε), otherwise equals 0. s_{LF} or s_{RF} equals 1 if more than two markers on the left/right foot are close to the ground, equals 0.5 if one or two left/right foot markers are close to the ground, otherwise equals 0.We shall show how to compute torque for non-supporting limbs in the rest of this section.

Arm / Leg Gravity Torque

We consider the arm as comprising two solid objects (forearm and upper arm) connected by the elbow joint (ref. Figure 5 (a)). Arm torque can be easily estimated by using marker positions. Let us denote the left shoulder marker as X_{LSHO}, left elbow marker as X_{LELB}, the centroid of 4 left forearm markers (X_{LELB}, X_{LFRM}, X_{LWRA} and X_{LWRB} in Figure 3) as X_{LFA}, the centroid of 3 left upper arm markers (X_{LSHO}, X_{LUPA} and X_{LELB}) as X_{LUA}. The left arm gravity torque T_{LA} is:

$$\begin{aligned} T_{LA} &= \frac{m_{UA}\cdot g\cdot d_2(X_{LSHO},X_{LUA}) + m_{FA}\cdot g\cdot d_2(X_{LSHO},X_{LFA})}{m_{UA}\cdot g\cdot d_3(X_{LSHO},X_{LUA}) + m_{FA}\cdot g\cdot [d_3(X_{LSHO},X_{LELB}) + d_3(X_{LELB},X_{LFA})]} \\ &= \frac{d_2(X_{LSHO},X_{LUA}) + (m_{FA}/m_{UA})\cdot d_2(X_{LSHO},X_{LFA})}{d_3(X_{LSHO},X_{LUA}) + (m_{FA}/m_{UA})\cdot [d_3(X_{LSHO},X_{LELB}) + d_3(X_{LELB},X_{LFA})]} \ , \end{aligned} \tag{6}$$

where m_{UA} and m_{FA} are mass of upper arm and forearm respectively, we know the ratio m_{FA}/m_{UA} equals 0.723 [5], g is acceleration of gravity, $d_2(\bullet)$ and $d_3(\bullet)$ are L_2 distance measurement in X-Y plane and X-Y-Z 3D space. Here, we only consider the magnitude of the torque and ignore the direction. This is because the effort on the corresponding joint is proportional to the magnitude of the gravity torque.

The torque in (6) is a normalized torque. The denominator is the maximum torque for arm which equals the torque when the arm is horizontally stretched. In a similar manner, we can also obtain right arm gravity torque T_{RA}. Hence, the overall arm gravity torque is defined as the scalar sum of the two arm torques:

$$T_A = u(s_{LH} + s_{LA}) \cdot T_{LA} + u(s_{RH} + s_{RA}) \cdot T_{RA} \, , \tag{7}$$

where T_{LA} and T_{RA} are left and right arm gravity torque respectively, s_{LH}, s_{LA}, s_{RH}, and s_{RA} are supporting indicators of left hand, left arm, right hand and right arm respectively, $u(\cdot)$ is standard step function. If $s_{LH}+s_{LA}>0$ which means left arm is supporting limb, left arm torque T_{LA} should be incorporated in effort computation. In the similar manner, we can determine if right arm torque T_{RA} should be considered.

In a similar manner to arm gravity torque computation (ref. equation(6) and (7)), we can compute the left leg gravity torque T_{LL} and right leg gravity torque T_{RL} and overall leg gravity torque T_L (ref. Figure 5(b)).

Torso Gravity Torque

Computing torso gravity torque (T_T) differs with computing arm or leg torque. If the torso is lying on the floor or if the supporting limbs include both arm and leg, the torso torque equals zero (T_T =0). If the body is supported only using the arms (ref. Figure 5 (d)), the torso torque is with respect to the shoulder ($T_T = T_{T\text{-}SHO}$). If the body is supported only using legs or the hip (ref. Figure 5 (c)), the torso torque is with respect to the hip ($T_T = T_{T\text{-}HIP}$). The torso torque with respect to shoulder ($T_{T\text{-}SHO}$) and the torso torque with respect to hip ($T_{T\text{-}HIP}$) can be computed as follows:

$$T_{T-SHO} = \frac{d_2(X_{SH}, X_T)}{d_3(X_{SH}, X_T)}, \quad T_{T-HIP} = \frac{d_2(X_W, X_T)}{d_3(X_W, X_T)} \, , \tag{8}$$

where X_W is centroid of four waist markers, X_{SH} is centroid of 2 shoulder markers, X_T is the centroid of 5 torso markers.

4.2 Supporting-limb effort

We now present an algorithm to compute supporting-limb effort. Intuitively, the human puts effort on the limbs in contact with the ground (supporting limbs) to support the body. This effort is related with the supporting limb power. The supporting limbs with large supporting power will decrease the amount of effort required holding the pose. Therefore, we estimate supporting-limb effort by combining the estimation of all supporting limb power.

Using supporting-limb vector (equation (5)), we can estimate the power of supporting limbs heuristically. The left arm supporting power p_{LA} is computed by:

$$p_{LA} = \begin{cases} s_{LH} \cdot \alpha_{A1}(1 + \sin|\theta_{LE} - \frac{\pi}{2}|) & if \ s_{LA} = 0 \\ \alpha_{A2} & if \ s_{LA} \neq 0 \end{cases} \, , \tag{9}$$

where s_{LH} and s_{LA} are supporting indicators of left hand and left arm respectively, θ_{LE} is left elbow angle and α_{A1} and α_{A2} are two constant weights ($\alpha_{A1}>\alpha_{A2}$). We consider the supporting using the whole arm and hand supporting separately, since hand supporting has more power than laying the whole arm on the ground. If the left arm lies on the ground ($s_{LA}\neq 0$), the supporting power is a constant α_{A2}, otherwise the supporting power of the left arm is related with s_{LH} and θ_{LE}. If s_{LH} equals 1 which means that the left hand is in contact with the ground, as the elbow angle θ_{LE} comes close to 90 degrees, the supporting power of the left arm decreases. We can obtain the right arm supporting power p_{RA} in the similar manner.

We can also compute the leg supporting power p_{LL} in the similar manner:

$$p_{LL} = \begin{cases} s_{LF} \cdot \alpha_{L1}(1 + \sin|\theta_{LK} - \frac{\pi}{2}|) & \text{if } s_{LL} = 0 \\ \alpha_{L2} & \text{if } s_{LL} \neq 0 \end{cases}, \tag{10}$$

where s_{LF} and s_{LL} are supporting indicators of left foot and left leg respectively, θ_{LK} is left knee angle and α_{L1} and α_{L2} are two constant weights ($\alpha_{L1}>\alpha_{L2}$). We can obtain the right leg supporting power p_{RL} in the similar manner.

The torso support power p_T and hip support power p_H are defined as:

$$p_T = s_T \cdot \alpha_T, \quad p_H = s_H \cdot \alpha_H, \tag{11}$$

where s_T and s_H are supporting indicators corresponding to torso and hip respectively and α_T and α_H are two constant weights. The values of α_{A1}, α_{A2}, α_{L1}, α_{L2}, α_T and α_H are determined by heuristic intuition that torso and hip have more power than legs and legs have more power than arms. Hence we heuristically set $[\alpha_{A1}, \alpha_{A2}, \alpha_{L1}, \alpha_{L2}, \alpha_T, \alpha_H]^T=[0.03, 0.02, 0.25, 0.2, 0.9, 1]^T$.

We postulate that the supporting limb power is additive. Hence, the overall supporting limb power p of a pose is the summation of power of all supporting limbs:

$$p = p_{LA} + p_{RA} + p_{LL} + p_{RL} + p_T + p_H. \tag{12}$$

The supporting limb effort is inversely proportional to the overall supporting limb power p. However, if the overall supporting power of the pose is large enough, the supporting limb effort difference between two poses is very small. Hence, we compute a thresholded supporting effort E_s as follows:

$$E_s = (1 - \frac{p}{\beta}) \cdot u(\beta - p), \tag{13}$$

where p is the overall supporting limb power, β is a predefined threshold and $u(\cdot)$ is standard step function. If p is larger than β, the overall supporting limb effort is zero.

5 Effort Estimation Using SVM Regression

Combining the five physical limitations, three limb torques and supporting-limb effort, we can construct a feature vector for every pose:

$$F = [d_F^\gamma, \theta_F^\gamma, \theta_E^\gamma, \theta_A^\gamma, \theta_R^\gamma, T_A^\gamma, T_L^\gamma, T_T^\gamma, E_s^\gamma]^T \ , \tag{14}$$

where d_F, θ_F, θ_E, θ_A, θ_R, T_A, T_L, T_T and E_s are foot distance, hip flexion, hip extension, hip abduction/adduction, hip rotation, arm gravity torque, leg gravity torque, torso gravity torque and supporting limb effort respectively, γ is a constant. It is easy to know that as feature (e.g. foot distance) increases, the effort required increases non-linearly. Hence, γ should be larger than 1. In the experiment, we select γ=1.5.

In order to estimate the effort by using all extracted features, we use SVM regression [7] to combine all features together. In training phrase, each training pose is represented by a feature vector F (eq(14)) and an annotated effort value which is considered as the ground truth G. The goal of SVM regression is to find a function $g(F)$ that has at most ε deviation from the ground truth G for all the training data, and at the same time is as flat as possible. The function g takes the form:

$$g(F) = K(w, F) + b \ \ with \ w \in \Omega, b \in R \ , \tag{15}$$

where Ω denotes the space of the pose effort feature vector, $K(\cdot,\cdot)$ denotes a kernel operator (e.g. linear, polynomial or rbf (radial basis function)). Flatness in the case of (15) means that one seeks a small $\|w\|$. The appropriate w and b can be obtained by solving a standard optimization problem [7]. In testing phrase, effort estimation includes two steps: (a) extract feature vector F (eq. (14)) and (b) estimate effort use SVM regression model obtained in training phrase by:

$$E = g(F) = K(w, F) + b \ , \tag{16}$$

where w and b are the solution of SVM regression on the training dataset.

6 Experiments

We test our human effort estimation algorithm on a dance pose dataset which includes 55 annotated poses. Each pose is annotated with an effort value from zero to five by one of the authors who is an expert in dance and kinesiology. Zero means no effort and five means maximum effort for human to hold a pose. She made these annotations when she held these poses by herself. These annotations are made by her real experience rather than through visual impression of the poses (e.g. through watching video of the poses). These 55 poses include 6 levels (0-5), 5 poses for each level (different poses that have the same effort) and 5 variation poses between consecutive levels. This is a fine grained estimation of physical effort by an expert.

In our experiments, we select one pose as testing data and other 54 poses as training dataset and compute leave-one-out cross validation to evaluate our algorithm. With 54 training poses, we can train a SVM regression model and apply it on the testing pose to estimate the effort. We repeat this process until every pose is selected as testing data and its effort estimation value is obtained. Hence, we can compute the difference between estimation value and ground truth to evaluate our algorithm.

6.1 Evaluation

Let us denote the effort ground truth of 55 poses as G_i, *i=1,…,55*, and the effort estimation results obtained by using our algorithm as E_i, *i=1,…55*. Hence, the estimation error is defined as the mean square root error:

$$err = \sqrt{\frac{1}{55}\sum_{i=1}^{55}(E_i - G_i)^2}\ . \tag{17}$$

In this paper, we use the estimation error to evaluate our algorithm, the smaller the error is, the better performance our algorithm has.

6.2 Experiment Results

In our experiments, we try 3 kernels in SVM regression – (a) linear kernel, (b) polynomial kernel and (c) rbf kernel. For each kernel, we adjusted maximum acceptable deviation ε, trade-off constant C and kernel parameter (e.g. the degree of polynomial kernel or the gamma of rbf kernel) to minimize the estimation error. We observe that polynomial kernel is better than both the linear kernel and rbf kernel in our experiments. Using the polynomial kernel, the estimation error is minimized when $\varepsilon=10^{-7}$, $C=27$ and polynomial power = 2. The mean absolute deviation from ground truth is 0.204. The standard deviation (eq.(17)) is 0.295.

Figure 6 shows eleven dance poses in increasing order of effort. For each pose, we show the effort ground truth (*G*) and our estimation result (*E*). It is easy to observe that our estimation efforts are very close to the ground truth value.

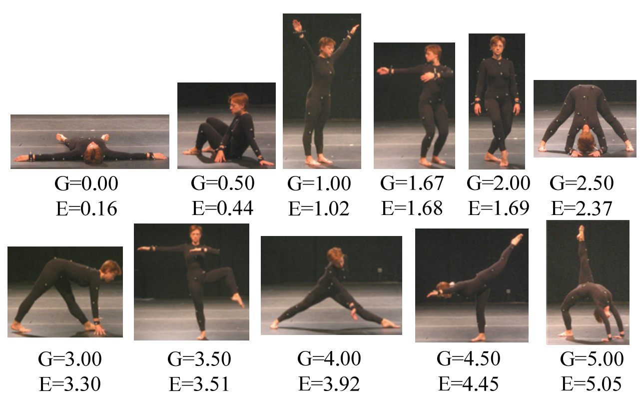

Figure 6. Effort estimations for 11 dance poses. G is ground truth effort and E is our estimation results.

Figure 7 plots the ground truth and our estimation efforts for all 55 poses. We can see that estimation efforts are close to the ground truth values for most poses. The maximum deviation larger than the ground truth is d_1=0.627 and the maximum deviation less than the ground truth is d_2=0.873.

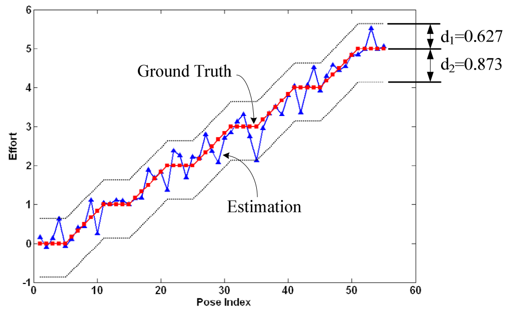

Figure 7. Comparisons between ground truth and effort estimation for 55 poses.

6.3 User Studies

We conducted user studies to determine the relationship between our computational pose effort measure and human perception of the physical experience. A group of 11 subjects with different backgrounds were presented with 50 pairs of pose images that were randomly selected from the 55 annotated poses. They were then asked to determine if the first pose A (on the left) needs more effort than the pose B (on the right). To enable this, we presented the users with seven statements – "pose A needs much more effort than pose B", "… more effort…" etc. The user could only mark one statement to be true. Then we mapped an integer from -3 to 3 to each test pair as *perceptual effort difference* (PED) between two poses. Positive integer means the first pose needs more effort than the second pose and vice versa. Large absolute values of the PED imply greater perceptual effort differences between the poses.

We classified the 550 shape pairs in the user studies into 7 classes based on the PED assigned by users and computed the average *estimate effort difference* (EED) for each class using Eq.(16) (shown in Figure 8 (a)). The figure shows that our computational effort measure (using EED) is highly correlated with the perception of the effort difference. Figure 8 (b) shows sensitivity curve. The region above the curve is the differentiable region – i.e. with probability greater than 97%, for poses whose *estimate effort differences* (EED) lie in that region are differentiable by the user. The difference threshold is small for poses with small effort.

The user studies indicate two clear results (a) our estimation of physical effort is correlated with human perception and physical experience, (b) the sensitivity to the effort difference is proportional to the effort of the pose that has larger effort – i.e. *user always compare the pose which has smaller effort with the pose which has larger effort.* Intuitively this means that people can use small pose effort differences to distinguish amongst poses with small effort, and require large differences in effort to tell apart poses with significant effort. As part of our future work, we plan to use effort based techniques to summarize human dance movement.

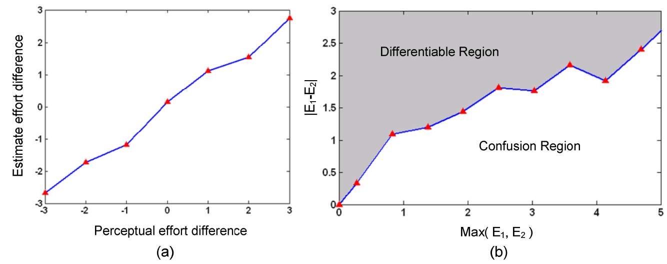

Figure 8. Relationship between perceptual effort and our computational effort estimation. (a) EED-PED curve, (b) sensitivity curve showing the differentiable region (dark) and the region of confusion (light). Two poses with pose effort difference in this dark region can be differentiated with high probability.

7 Conclusion

In this paper, we have presented a human pose effort estimation algorithm based on SVM regression. There are two key innovations (a) Using both skeletal constraints and gravity constraints to estimate human pose efforts, (b) Using SVM regression algorithm to combine features for effort estimation. We evaluated our framework on 55 annotated dance poses. Our experimental results are excellent with mean square root error 0.295. In the future, we are planning to incorporate our pose effort framework into pose recognition algorithms. We also planning to incorporate pose effort into dance summarization applications.

Reference

[1] S. BELONGIE, J. MALIK and J. PUZICHA (2002). *Shape matching and object recognition using shape contexts.* IEEE Transactions on Pattern Analysis and Machine Intelligence **24**(24): 509-522.

[2] Y. CHEN, H. HUANG, W. XU, et al. (2006). *The Design Of A Real-Time, Multimodal Biofeedback System For Stroke Patient Rehabilitation*, SIG ACM Multimedia, Santa Barbara, CA, Oct. 2006.

[3] D. FORSYTH and J. PONCE (2003). Computer vision : a modern approach. Englewood Cliffs, N.J., Prentice Hall**:** xxv, 693.

[4] H. HUANG and Y. CHEN (2005). *Marker Setup and Parameter computation for biofeedback system*. AME Program, Arizona State University, AME-TR-2005-20, 2005.

[5] K. KAHOL, P. TRIPATHI and S. PANCHANATHAN (2003). *Gesture segmentation in complex motion sequences*, ICIP 2003, Barcelona, Spain, Sept 14-17, 2003.

[6] R. LABAN (1971). The Mastery of Movement. Boston, Plays.

[7] A. J. SMOLA and B. SCHOLKOPF (2004). *A tutorial on support vector regression.* Statistics and Computing **14**: 199-222.

[8] L. ZHAO and N. I. BADLER (2005). *Acquiring and validating motion qualities from live limb gestures.* Graphical Models **67**(1): 1-16.