

Realistic collision avoidance of upper limbs based on neuroscience models

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Abstract

When articulated figures interact in a 3D environment, collisions are highly likely and must often be avoided. We present a method automatically producing realistic collision-free animation of the upper arms. Based on the latest models of collision avoidance provided by neuroscience, our method allows realistic interpolation of keyframes at interactive speed. In order to validate our scheme we compared computer generated motions with motions performed by a sample of ten humans. These motions were defined by start and final postures and by an obstacle which had to be passed. In each case the generated positions are the same as those chosen by 30% of real humans, we therefore consider our method provides realistic motions. Moreover, the collision-free paths are automatically generated in a few seconds. Hence, our method can be very beneficial to animators by reducing the level of detail needed to define motions of articulated figures. It can also be used for the automatic generation of realistic animations for virtual reality applications.

1. Introduction

Since the release of the first fully computer-animated feature film "Toy Story" in 1995, animation films have become more and more popular. All of them feature articulated characters whose motions are choreographed by animators defining keyframes. These keyframes are interpolated and the motions generated are then adjusted as necessary by the animators¹⁶.

When these articulated figures interact in a 3D environment, collisions are highly likely and must often be avoided. Animators may be asked to provide a higher level of detail to ensure that the interpolation curves produce the desired motion. This is very time consuming and distracts from the creation process. Hence the automatic generation of collision-free paths is an active field of investigation which has been addressed in many different ways. For physically based animations collisions are detected and reactions are computed^{29,4}. In robotics many exact solutions exist to produce collision-free motions. However, since the complexity grows exponentially with the number of Degrees of Freedom (DOFs) their use is practically impossible on a simulated human⁹. Hence schemes that are not *complete*³² (may fail to find a path when one exists) or probabilistically *complete*⁵

have been developed which makes the task feasible though still time consuming. Other papers deal with achieving collision avoidance when articulated figures animated using inverse kinematics are reaching a goal^{33,15}. Collisions are detected using sensors and response vectors integrated into the inverse kinematics equation system. This process operates incrementally but does not ensure a coherent motion. Finally, a model of human visual collision perception has been developed to deal only with perceptible collisions¹⁹.

An animator using keyframe animation requires the generation of collision-free motions at interactive rates. The method does not have to be *complete* since the animator can intervene, but it has to respect the postures defined by the keyframes, and be realistic. Because none of the approaches presented previously responds to these constraints it was decided to explore another path, through the field of neuroscience. Using neuroscience models describing the movement of the human arm we propose an algorithm generating realistic collision-free paths for keyframe animation at interactive speeds.

Section 2 presents the neuroscience models on which our method is based. Section 3 shows how we exploit them. Then Section 4 gives the principles of our collision avoid-

ance method. Finally, Section 5 presents and discusses some experimental results.

2. Neuroscience models

Behavioural neuroscientists are interested in the processes underlying behaviour in humans and animals such as the means by which the *central nervous system* (CNS) controls movements. The problem is studied by determining what movement strategies are used.

Research into the processes by which the CNS coordinates the large number of degrees of freedom of movement of multi-joint limbs started during the late 60s⁶. However the first papers dealing with obstacle avoidance in the neuroscience literature date from the early 80s.

Abend *et al.*¹ studied human planar two-joint arm movements. They discovered that when subjects are asked to reach a target with the hand the paths are roughly straight and the hand speed profiles of their trajectories are bell-shaped. When subjects have to avoid an obstacle, though, their strategy is to move the hand on a straight path towards the end of the obstacle, then gently curve the path around the end of the obstacle and head directly to the target (Figure 1). In this case, Abend *et al.* showed that the hand speed profiles have peaks before and after passing the obstacle.

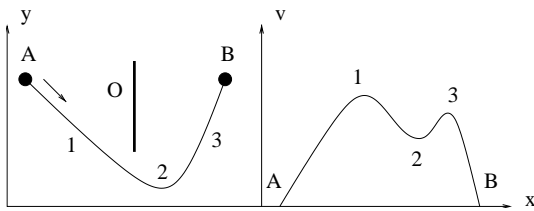


Figure 1: Path and velocity of the hand between A and B while avoiding an obstacle (O)

Also from arm motion, Flash and Hogan¹² proposed a mathematical model, the *minimum jerk model*, that simulates unconstrained point-to-point movements as well as curved point-to-point movements passing through a third specified point. This model is based on the minimisation of the rate of change of hand acceleration in a fixed Cartesian coordinate system. The integration of the derivation of hand acceleration gives a function C which has to be minimised, as:

$$C = \frac{1}{2} \int_0^{t_f} \left(\left(\frac{d^3x}{dt^3} \right)^2 + \left(\frac{d^3y}{dt^3} \right)^2 \right) dt$$

where t_f is the time needed to reach the final position.

Their model matches observed human planar two-joint arm movements and implies that trajectories are invariant under translation, rotation, time and amplitude scaling. Hence this research provides strong support for the hypothesis that movements are planned in terms of the motion of a “disembodied hand” moving in extracorporal space.

Dear and Bruwer¹⁰ studied three DOFs obstacle avoidance, experimentally. They compared motions via a specified point with motions in avoiding an obstacle; their paths appeared to be similar. Moreover, their analysis of the path near the obstacle concluded that the movement was composed of two independent parts. Hence, it could be assumed that path planning involves an intermediate point near the obstacle^{1,12}. Because the position of the turning point is generally different from the point closest to the obstacle (Figure 1), the intermediate point could not be specified.

They noticed also that contrarily to the prediction of the *minimum jerk model*, trajectories are not quantitatively invariant under translation or rotation, as the position of the closest point changes. Their research implies that path planning for obstacle avoidance does not use a fixed coordinate system alone¹², but joint-space parameters too.

Sabes *et al.*^{23,24} addressed the issue of how the intermediate point would be chosen. At first, they determined that the trajectory of the hand is a function of obstacle orientation. Therefore they suggested, as Dear and Bruwer¹⁰ did, that properties of the arm should be taken into account too. Then they looked for a way of expressing the constraint of obstacle avoidance. Hence, they studied the sensitivity of the arm at the closest point of the trajectory; the sensitivity should be minimum with regard to uncertainty or perturbations in the direction of the obstacle. Their *sensitivity model* is based on the inertial properties of the arm. The definition of sensitivity they used was proposed by Hogan^{13,14}, who expressed the *mobility matrix* of the arm in end-point coordinates, $W(\theta)$, as:

$$W(\theta) = J(\theta)Y(\theta)J^t(\theta) \quad (1)$$

$$I^{-1}(\theta) = Y(\theta) \quad (2)$$

where $Y(\theta)$ is the *mobility matrix* of the arm in actuator coordinates. $I(\theta)$ is the inertia matrix of the arm in actuator coordinates and $J(\theta)$ is the Jacobian.

The physical meaning of the *mobility matrix* is that if the system is at rest an applied force F will produce an acceleration a equal to the force vector premultiplied by the *mobility matrix*: $a = WF$.

Since the *mobility matrix* is symmetric it may be diagonalised by rotating the coordinate axes to coincide with its eigenvectors. It may be represented graphically by an ellipsoid as in Figure 2. The eigenvectors of W have a simple interpretation: the major (minor) eigenvector is the direction along which force perturbations have the largest (smallest) effect. Thus, the *sensitivity model* predicts that the near points should cluster toward a preferred axis which is the *mobility minor axis*.

The prediction of the *sensitivity model* shows close agreement with the results of the obstacle avoidance experiment in two dimensions²³ as well as in three dimensions²⁴. When

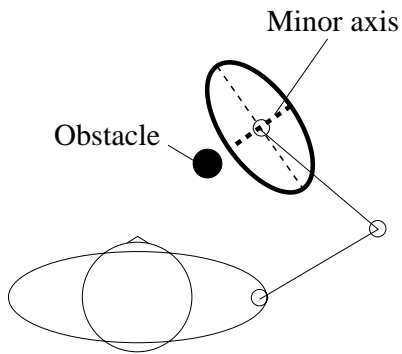


Figure 2: Mobility ellipse in the plane

the hand is closest to the obstacle, its position is along the preferred axis (Figure 2) which ensures the arm is in the best configuration for avoiding collisions.

Although in their experiments participants were asked to avoid obstacles with their fingertip only, Sabes *et al.*^{23, 24} are confident that their model could be extended in order to deal with more general obstacle avoidance.

3. Exploitation of the neuroscience models

In the previous section, we reviewed the state-of-the-art in the understanding of collision avoidance by neuroscientists. We first summarise what seems to be essential and propose extrapolations of these models to make them applicable for our purpose. Then we give some details about how we calculate the *mobility* matrix and how it is analysed.

3.1. Extrapolations

Dear and Bruwer¹⁰ showed that if there is a simple obstacle between a starting point and a target point, the CNS seems to add an intermediate point near the obstacle through which the path of the hand will go. Flash and Hogan¹² by their *minimum jerk model* described the path connecting these three points and showed the path is actually the combination of two point-to-point trajectories. Since a keyframe animation is a path between a list of keyframes, the posture at the intermediate point may be seen simply as one more keyframe. So once an intermediate position is found, we create a new keyframe that will be treated the same way as the others.

A remaining problem is how to find the intermediate position. The neuroscience papers give us some clues. The *sensitivity model*^{23, 24} provides a fundamental property about the closest point: it corresponds to a position where the arm is least sensitive to perturbations. An infinite number of positions have this property. Moreover, despite the fact that the closest point and the intermediate point may be distinct but close¹⁰, we consider the two points to be similar. We make

this approximation mainly because we do not have any information about this intermediate point. Experimental results will tell us if this approximation is valid or not (Section 5). In order to find the intermediate point, we get a list of potential intermediate positions for obstacle avoidance as proposed by the author¹⁸, and then select one with the best sensitivity property.

The validity of the *sensitivity model* has been verified only with the task of collision avoidance limited to the fingertip rather than with the entire arm. However, we assume it is valid in the general case too. The main uncertainty about this model is how to deal with cases where the main task is not to avoid an obstacle with the end-effector but with another joint such as the elbow. Unfortunately there are no studies on the subject so we must extrapolate from the models previously discussed.

It seems that when a human wishes to avoid an object with their hand they focus on its trajectory using the “disembodied hand” model¹² which is controlled in the manner described by the *sensitivity model*. Hence it seems sensible to use the same model if the focus is on avoiding the collision between the elbow and an obstacle. But in this case it would be the *mobility* of the elbow which should be studied instead of that of the hand. Experiments with this extrapolation of the model show its correctness (Section 5).

Consequently for our purposes, depending on which kind of collisions should be avoided, the *sensitivity model* is used either for the hand or the elbow.

3.2. Mobility matrix

The *sensitivity model* is based on an analysis of the *mobility* matrix of the end-effector. According to equations 1 and 2 in Section 2 the computation of this matrix depends on the values of the Jacobian matrix of the end-effector, J , and the inertia matrix of the arm in actuator coordinates, I .

Let n be the number of DOFs of the arm and q be a vector which represents the n joint angles of the arm. If e is the position of the hand in the end-effector coordinates, then the Jacobian matrix of the end-effector is the following $nx3$ matrix:

$$J(q) = \frac{\partial e(q)}{\partial q} \quad (3)$$

Before giving the expression of the manipulator inertia matrix $I(q)$, we need to introduce the definition of the *manipulator Jacobian*²⁵ M^i for a joint i . Since it is based on the notion of infinitesimal translations and rotations of a limb, it is usefully partitioned into two $3xn$ blocks, A^i and B^i , as follows:

$$M^i(q) = \begin{bmatrix} A^i(q) \\ B^i(q) \end{bmatrix} \quad (4)$$

Thus A^i is associated with linear displacement, while B^i is

associated with angular displacement. Let c^i represent the position of the centre of mass of the limb associated with the joint i in end-effector coordinates. Then A^i is:

$$A^i(q) = \frac{\partial c^i(q)}{\partial q} \quad (5)$$

For a rigid skeleton the expression of B^i is:

$$B^i(q) = R_0^i(q)[0, 0, 1]^T \quad (6)$$

where the rotation matrix $R_0^i(q)$ represents the orientation of coordinate system of the joint i relative to the one of the joint 0.

Let D_i denote the inertia matrix of the limb associated with the joint i in end-effector coordinates and m_i express the mass of that limb. If I_i is the contribution to the manipulator inertia matrix from joint i , the manipulator inertia matrix is the following $n \times n$ matrix:

$$I(q) = \sum_{i=1}^n I_i(q) \quad (7)$$

where

$$I_i(q) = (A^i(q))^T m_i A^i(q) + (B^i(q))^T D_i(q) B^i(q) \quad (8)$$

In order to simplify the inertia matrix of the arm which has seven DOFs, as Sabes *et al.*²⁴ proposed the joints of the wrists are not considered. The potential displacement of their centres of gravity can be neglected with respect to those of the forearms and the upper arms. Moreover, motions of the wrists are less important in the collision avoidance process¹⁰. Hence hands are seen as extensions of forearms when the matrix is calculated. I is then a 4×4 symmetric matrix whose expression of the coefficients needs still more than 34 Kb of storage.

The expression of I entails knowledge of the inertia matrices of the limbs composing the arm. They depend on how the geometry of each limb is expressed: mass point, rod, cylinder or more complex models. Then depending on the chosen geometry, data such as length, weight, radius or centre of mass may be needed. The anthropometric data used corresponds to the 50th percentile of British adults between 19 and 65 years^{20, 21}.

Once the *mobility* matrix has been computed, the preferred axis can be obtained by the computation of the Eigenvalues and the Eigenvectors of W . Since the *mobility* matrix is a symmetric matrix all the Eigenvalues are real. If there is no double Eigenvalue, the Eigenvectors of W define the ellipsoid of *mobility* where the Eigenvector corresponding to the smallest Eigenvalue gives the direction of maximum inertia (minimum *mobility*). Otherwise the maximum inertia can be defined by a vector, a plane or even the whole space depending if the ellipsoid is respectively an oblate spheroid, a prolate spheroid or a sphere.

4. Principles of the collision avoidance method

Now that we have explained the limits of and the extension to the neuroscience model we show how to use it in order to generate realistic collision-free animation, automatically, at interactive speed.

4.1. Main principle

In this study an articulated body is defined as a hierarchy of rotational joints each having up to three DOFs²⁷ limited to believable postures. Keyframes can be created by an animator or selected from previous motion. Once keyframes have been specified, interpolations are achieved to produce the animation. The task we deal with is to offer an interpolation algorithm which generates collision-free motions.

The principle of our scheme is to first detect the objects that should be avoided. An interpolation between keyframes is performed using any classical inbetweening method such as cubic splines that can be controlled using kinematics^{26, 17} or dynamic constraints^{22, 3}. Collisions are sorted and the dominant one is selected for a specific time step (Section 4.2). This collision is corrected first. At this time step the frame is modified automatically to generate the intermediate keyframes using geometrical and *mobility* properties, as in the next section. Finally, this new keyframe is used for a new classical interpolation. This process continues until a collision-free motion is obtained.

The following is an outline of the algorithm providing a collision-free motion between two keyframes (K_0 and K_1) specified at the times (T_0 and T_1).

```

CheckAndCorrect( (K0, T0), (K1, T1) )
{
    Interpolate between K0 and K1
    Get the list of collisions for each time step
    If(collision)
    {
        Select the first collision to be corrected, (Col, TCol)
        Move the limbs at TCol to intermediate position
        Create an intermediate keyframe (KCol, TCol)
        CheckAndCorrect( (K0, T0), (KCol, TCol) )
        CheckAndCorrect( (KCol, TCol), (K1, T1) )
    }
}

```

This algorithm does not make any hypothesis about the kind of objects which compose the articulated figure, only a rigid skeleton is needed. So regardless of the way the articulated figure is defined, our scheme can be used to generate animations without collisions for any collision detection algorithm.

4.2. Generation of an intermediate keyframe

To generate an intermediate keyframe, we must find the dominant collision and the time step at which the correction

has to occur. We define a dominant intersection as a collision whose correction suppresses the largest number of collisions. Practically, we sort all the collisions produced by the interpolation and select the one which occurs for the longest duration. The time step chosen for the correction is the centre of this period. Thus we get a specific time step to correct the collision between an obstacle and a limb. Before starting the correction process, we look for any related intersections at the same time step. If there are other intersections between the selected arm and the obstacle, we have to correct them during the same process. One should define what task of collision avoidance the brain would plan. We assume that in this case the brain would focus on the task of avoiding the collision between the obstacle and the intersected limb whose extremity is closest to it.

Once the time step and collision avoidance tasks have been specified, the correction process can start. The position of the joints of the arm is used as a starting point for identification of an intermediate posture. Since the interpolation algorithm has been chosen to provide realistic motions, we would like the generated collision-free motion to keep most of the properties of the first interpolation. Hence any newly generated position of a limb should be closely related to the previously interpolated curve. Moreover we want the arm position to comply with the *mobility* criterion (Section 3.1).

In order to fulfill these constraints we first get a set of positions of the arm based on the interpolated paths and geometrical properties according to the algorithm described in¹⁸. Positions that are not collision-free, break the DOF limits or are not close enough to the obstacle are discarded. The *mobilities* of valid positions are tested. The most stable position of the arm is used to create an intermediate keyframe.

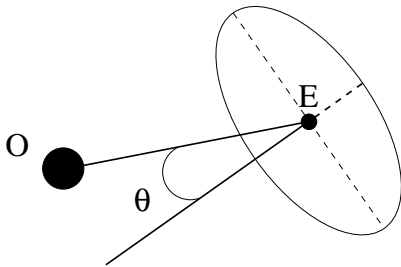


Figure 3: Divergence from the preferred axis

For each test, the *mobility* matrix is computed with respect to the limb extremity whose stability is under consideration. Then according to the type of ellipsoid the matrix defines, the angle θ or *divergence*, between the preferred axis (or plane) and the segment joining the extremity of the limb, E , and the obstacle is calculated (Figure 3). Depending on time and precision constraints, the user can specify the tolerable *divergence* limit regarding the *mobility* of the position of the arm. For smaller values of θ , the position is more stable.

submitted to EUROGRAPHICS 2000.

5. Experiments and discussion

To evaluate the model, animations produced by our method are compared with motions performed by participants. Although interpolation^{26, 22, 3, 17} or time wrapping^{31, 28, 8} techniques may be necessary to reach the highest degree of realism or to personalise motions, we will not discuss them in this paper. These comparisons are focused on the intermediate postures, because the success of a realistic animation depends, at first, on the choice of keyframes. We first describe the setting of these experiments, then we present some results and discuss them.

5.1. Procedure

The evaluation of the realism of motions generated by computers is a difficult and often subjective task. In order to solve this problem we decided to compare these motions with movements performed by human beings. Hence our experiments consist of two parts. The first is the generation of collision-free paths using our algorithm. The second is to ask people to avoid obstacles.

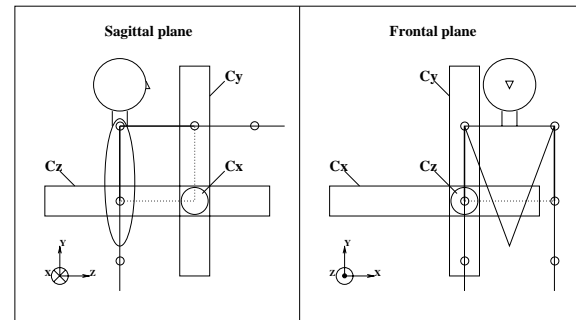


Figure 4: Positions of the cylinders (C_x , C_y and C_z) used for the obstacle avoidance experiments

In both cases the motions are defined by two postures chosen to be easily reproduced by our character as well as by the participants of the “live” experiment. The obstacle is a cylinder lying along either the X, Y or Z axis and with radius 4 cm. Positions are defined as described in Figure 4. The length unit used for placing the obstacle depends on the participant, and is defined as the length of their upper arm. In order to make comparisons possible we studied motions which are composed of a starting posture and a final posture and such that the obstacle can be passed with only a single intermediate posture.

For computer generation, a 75 MHz SuperSparc processor of a Sparc 20 workstation was used. In order to represent a human character an articulated figure composed of 19 limbs and 15 joints was used, whose properties correspond to an average British adult^{20, 21}. All interpolations were made using a classical cubic spline scheme and the inertia matrices of the limbs composing the arm are expressed using the rod

geometrical model. After having specified two key frames and the position of the obstacle, a collision free animation composed of 20 frames was generated automatically. As no *divergence* limit has been specified the intermediate position selected is the most stable of the valid positions.

Fifteen participants, two left-handed and thirteen right-handed, took part in the experiment, none of them being involved in our research. All participants had normal or corrected to normal vision. Three dimensional movements were recorded with two video cameras in the frontal (X-Y) and sagittal (Y-Z) planes (Figure 4). Since we are only interested in visually realistic motions, the analysis of the real motions is qualitative only.

The participants were first asked to hold a posture defined by the rotations of the upper arm and the forearm of a specific arm (Figure 5). They were then asked to reach a target with this arm avoiding the obstacle. This target was held by the hand of the other arm. The number of trials for a session was limited to 10 per participant and the number of participants was fixed at 10, one of them being left handed (approximately 10% of the general population is left handed). After a phase of warming-up which lasted around 5 seconds, participants were asked to perform their task at normal speed in a comfortable way.

5.2. Results

In this section, we present results for three cases, with the obstacle along each of the three axes (Figure 5), which are representative of our experiments. The collision-free paths automatically generated using our model were computed in a few seconds. Whatever the case participants performed their tasks easily. The motions of each subject in each session were very homogeneous and collisions with the obstacle were rare.

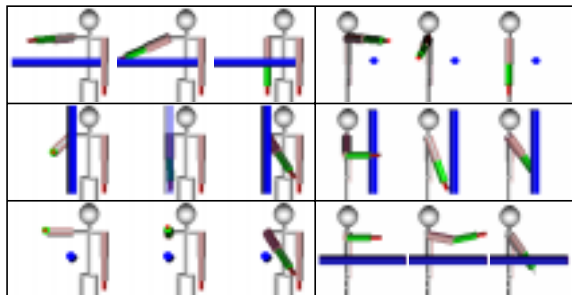


Figure 5: Starting, intermediate and final positions of our figure in the frontal and sagittal and planes (from top to bottom: Cx, Cy and Cz experiments)

For each case the intermediate positions of the ten participants are compared with the intermediate position generated using our method (solid lines) (Figures 6, 8 and 9).

The first task we study is the avoidance of the cylinder Cy (second row in Figure 5). Out of the ten positions (Figure 6), we could extract two main behaviours: passing the obstacle with the arm extended (3 participants) as our model predicted and passing the obstacle with the hand close to the navel (three participants). Two subjects had a position which was a combination of the two positions previously described and finally two subjects had very individual positions.



Figure 6: Intermediate positions of the participants in the sagittal plane while avoiding Cy

The angle between the arm and the vertical in the sagittal plane for the subjects who passed the obstacle with the arm extended was very close to the one generated by our model, only a few degrees at the most (Figure 6).

In Figure 7, we compare in the frontal plane the positions of the three subjects who passed the obstacle with the arm extended, with the position of the arm of our figure (solid lines). Since the intermediate position is hidden by the obstacle in this plane, positions on both sides of the obstacle are given for our subjects (dashed lines). In this plane, the generated position appeared to be compatible with the positions of our subjects too.

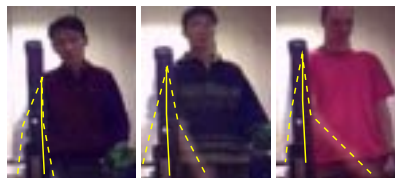


Figure 7: Intermediate positions of some participants in the frontal plane while avoiding Cy

In the second case, a collision between the elbow and the cylinder Cz should be avoided (third row in Figure 5). The first experiments required the participants to perform this task with their right arm. There was no correlation between

the intermediate positions of the participants and the computer generated one, except for the sole left handed subject. Moreover, some participants made motions which collided with the obstacle. We repeated the experiment asking the participants to avoid the obstacle using their left arm.



Figure 8: Intermediate positions of the participants in the sagittal plane while avoiding Cz

Two main behaviours were noticeable among the participants (Figure 8). The first behaviour was similar to that generated by our model. The task was performed in two clear steps: passing the obstacle safely and then going toward the goal. Out of the ten participants, four of them chose this approach. The alternative was to complete the task in only one step combining the two subtasks. This was the choice of four subjects. Finally two subjects chose a position which was a combination of the two positions previously described. The analysis in the frontal plane of the intermediate positions of the participants following the first behaviour showed that their arm had a position in the plane defined by the obstacle and their shoulder as expected by the model.

The last case presented deals with the avoidance of Cx (first row in Figure 5). In Figure 9, the intermediate positions seen in the sagittal plane are compared with the computer generated posture (solid lines).

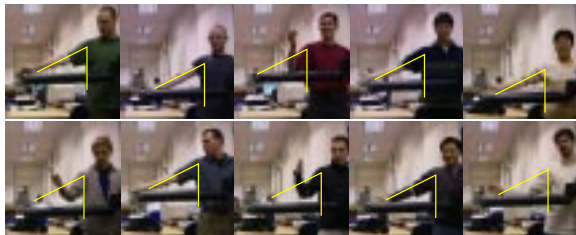


Figure 9: Intermediate positions of the participants in the sagittal plane while avoiding Cx

Most participants, six of them, avoided the obstacle in the way predicted by our model (Figure 9). But three of them looked for the shortest path and one of them had an intermediate strategy.

| Obstacle | Arm | Main behaviours | Similar to simulation |
|----------|-----|-----------------|-----------------------|
| Cx | R | 2 | 6 |
| Cy | R | 2 | 3 |
| Cz | R | 1 | 1 |
| Cz | L | 2 | 4 |

Table 1: Experimental results

In Table 1 we summarise the results provided by the previously described experiments. We report the type of obstacle, the arm used, the number of main behaviours observed and the number of participants, out of the ten participants, having an intermediate posture very similar to the position generated using our model.

5.3. Discussion

In the experiments described, the intermediate postures generated by our method can be considered realistic, since around a third of the participants had postures very similar to them (Table 1). However, some participants had very different postures.

We offer the following explanation for this: in each case of obstacle avoidance, two main behaviours were followed by the participants. In the first or “cautious” approach, motions were performed in two steps: passing the obstacle safely by reaching a stable intermediate posture and then going towards the final position. This approach was expected, since it fits the description of the neuroscience models. Hence unsurprisingly, the intermediate postures produced by the participants following this approach are well simulated by our method. But the second or “assertive” approach, does not seem to be as clearly composed of two steps. Our subjects seemed to avoid the obstacle trying to find the shortest path between the starting and the final positions. Hence the stability of the arm does not play a role as important as previously. This was highlighted in the experiment where participants were asked to avoid the obstacle Cz with their right arm. Apparently they did not find this task very challenging, so most of them adopted an “assertive” approach passing very close to the obstacle. They did this by reducing the stability of their arm while passing the obstacle which resulted, in some cases, with a collision. Apart from these two main approaches other behaviours could be observed. Most of them were intermediate positions that participants reached as a compromise between stability and a short path.

Although the tasks of collision avoidance tested were more complex than the ones studied in the neuroscience papers^{10, 23, 24} and some extrapolations and simplifications were needed (Section 3), our model could be validated for collision avoidance tasks which can be performed with a single intermediate position. We are confident that the motions generated with several intermediate positions (Section 4), are realistic too. However their validation was not addressed in this work due to the difficult problem that it represents.

Our model generating realistic collision free motion at interactive speed - a few seconds -, is very beneficial to animators. It is time saving, reducing the level of detail needed to define a motion. A trained animator needs between 30 and 60 seconds to produce a given pose with our articulated figure¹¹. It allows animators to focus more on the creation process. Our method could also be used for the automatic generation of animations for virtual reality applications, where the guarantee of collision free motions does not need to be absolute.

6. Conclusion and future work

We presented a model based on neuroscience results in order to generate automatically realistic collision-free motion of the upper limbs. Experimental results comparing a human model with real motions validated our algorithm showing that the generated motions are realistic, simulating the “cautious” way of avoiding obstacles.

Hence our method provides useful assistance for animators: they can generally reduce the level of detail needed to describe a movement and still get realistic motions at interactive speeds. Moreover our method could also be used for the automatic generation of realistic animations for virtual reality applications.

In the future we will work on simulating the “assertive” approach by using criteria based on minimum energy^{30, 7, 2} to select the intermediate postures. Then by combining this new model with our *mobility* model we should be able to personalise the motions. Depending on the weight given to stability towards minimum energy, we should be able to find the intermediate positions of a wide range of participants: from the most cautious ones to the most assertive ones. Finally our model could be extended to deal with lower limbs as well.

Acknowledgements

This work was supported by the European Union *Training and Mobility of Researchers* project “Platform for Animation and Virtual Reality”. We would like to thank members of the Faraday Laboratory of the University of Glasgow for their helpful comments and their participation in the experiments.

References

1. W. Abend, E. Bizzi, and P. Morasso. Human arm trajectory formation. *Brain*, 105:331–348, 1982.
2. R. M. Alexander. A minimum energy cost hypothesis for human arm trajectories. *Biological Cybernetics*, 76:97–105, 1997.
3. K. Arai. Keyframe animation of articulated figures using partial dynamics. In N. Magnenat-Thalmann and D. Thalmann, editors, *Models and techniques in computer animation*, pages 243–256. Springer-Verlag, 1993.
4. S. Bandi and D. Thalmann. An adaptive spatial subdivision of the object space for fast collision of animated rigid bodies. In *Eurographics’95*, pages 259–270, 1995.
5. J. Barraquand, L. Kavraki, J-C. Latombe, T-Y. Li, R. Motwani, and P. Raghavan. A random sampling scheme for path planning. *Journal of robotics research*, 16(6):759–774, 1997.
6. N. Bernstein. *The co-ordination and regulation of movements*. Oxford: Pergamon Press, 1967.
7. D. E. Breen. Cost minimization for animated geometric models in computer graphics. *The journal of visualization and computer animation*, 8:201–220, 1997.
8. M. F. Cohen C. Rose and B. Bodenheimer. Verbs and adverbs: Multidimensional motion interpolation. *IEEE Comp. Graphics and application*, 18(5):32–40, 1998.
9. J.F. Canny. *The complexity of robot motion planning*. MIT Press, 1988.
10. J. Dean and M. Bruwer. Control of human arm movements in two dimensions: paths and joint control in avoiding simple linear obstacles. *Experimental brain research*, 97(3):497–514, 1994.
11. S. Etienne. *Positioning articulated figures*. PhD thesis, University of Glasgow, 1998.
12. T Flash and N Hogan. The coordination of arm movements: an experimentally confirmed mathematical model. *Journal of Neuroscience*, 5:1688–1703, 1985.
13. N. Hogan. Impedance control: an approach to manipulation. *Journal of dynamic systems, measurement, and control*, 107:1–24, March 1985.
14. N. Hogan. The mechanics of multi-joint posture and movement control. *Biological cybernetics*, 52:315–331, 1985.
15. Z. Huang. *Motion control for human animation*. PhD thesis, EPFL-DI-LIG, 1996.
16. J. Kurtti. *A bug’s life*. Disney Enterprises Inc., 1998.
17. Z. Liu and M. F. Cohen. Keyframe motion optimization by relaxing speed and timing. In *1995 Eurographics Workshop on Animation*, Maastrich, Holland, 1995.
18. J.-C. Nebel. Keyframe interpolation with self-collision avoidance. In *Computer Animation and Simulation’99*, pages 77–86. Eurographics, Springer Computer Science, September 1999.
19. C. O’Sullivan, R. Radach, and S. Collins. A model of collision perception for real-time animation. In *Computer Animation and Simulation’99*, pages 67–76.

- Eurographics, Springer Computer Science, September 1999.
20. S. Pheasant. *Bodyspace: anthropometry, ergonomics and design*. Taylor and Francis, 1988.
 21. S. Pheasant. *Anthropometrics: an introduction*. British Standards Institution, 1990.
 22. X. Pintado and E. Fiume. Grafield: Field-directed dynamic splines for interactive motion control. In *Eurographics '88*, pages 43–54, 1988.
 23. P. N. Sabes and M. I. Jordan. Obstacle avoidance and a perturbation sensitivity model for motor planning. *Journal of Neuroscience*, 17:7119–7128, 1997.
 24. P. N. Sabes, M. I. Jordan, and D. M. Wolpert. The role of inertial sensitivity in motor planning. *Journal of neuroscience*, 18(15):5948–5957, 1998.
 25. R. J. Schilling. *Fundamentals of robotics: analysis and control*. Prentice Hall, 1990.
 26. S. N. Steketee and N. I. Badler. Parametric keyframe interpolation incorporating kinetic adjustment and phrasing control. In *Siggraph '85*, volume 19, pages 255–262, San Francisco, 1985.
 27. D. Sturman. Interactive keyframe animation of 3d articulated models. In S. MacKay, editor, *Graphics Interface '84*, pages 35–40, 1984.
 28. M. van de Panne. Parameterized gait synthesis. *IEEE Computer Graphics and application*, 16:40–49, 1996.
 29. P. Volino, N. Magnenat-Thalmann, S. Jianhua, and D. Thalmann. Collision and self-collision detection: Robust and efficient techniques for highly deformable surfaces. *Eurographics Workshop on Animation and Simulation*, 1995.
 30. A. Witkin, K. Fleischer, and A. Barr. Energy constraints on parameterized models. *Siggraph '87*, 21(4):225–232, July 1987.
 31. A. Witkin and Z. Popovic. Motion warping. In *Siggraph 95*, 1995.
 32. J. Kuffner Y. Koga, K. Kongo and J.-C. Latombe. Planning motions with intensions. In *SIGGRAPH '94*, pages 395–408, 1994.
 33. J. Zhao and N. I. Badler. Interactive body awareness. *Computer-aided design*, 26(12):861–867, 1994.