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Virtual Ergonomic Assessment on Handheld Products based on Virtual Grasping by Digital Hand

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ABSTRACT

The purpose of this research is to develop a system for virtual ergonomic assessment of products without real subjects and physical mockups by integrating a digital hand model with a product model. In previous work, we developed functions of a semi-automatic grasp planning for the digital hand and of quantitatively evaluating the grasp stability of the product based on the force-closure and the grasp quality in our system. We also confirmed the validity of the results from these functions by comparing them with the real grasp postures. However, only evaluating the grasp stability could not necessarily derive the appropriate grasp postures. To solve this problem, in this paper, we propose a new function of evaluating “ease of grasping (EOG)” for the grasp posture based on EOG-map constructed from principal component analysis for finger joint angles in real subjects’ grasps. We also developed another function of optimizing the grasp posture to avoid inappropriate postures by evaluating the posture similarity on EOG-map in the system.

INTRODUCTION

Recently, the manufactures of handheld information appliances have had to take more interest in ergonomic design to differentiate their products and to gain competitiveness in the market [1]. The ergonomic design of information appliances mainly has to be evaluated for two aspects: physical and cognitive. The physical aspect of the ergonomic design of these appliances includes easiness of grasping the housing, relevance of arranging the positions of physical components (buttons, switches, dials, displays lumps etc.) on the user-interface, and the ease of their manipulations. The assessment from the physical aspect usually requires subjects for a test and physical mockups of the appliance.

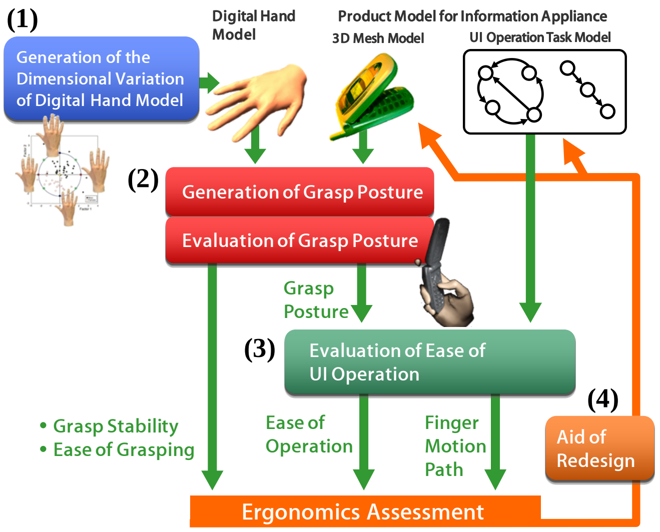


Figure 1. The overview of our proposed automatic ergonomic assessment system

However, the cost of fabricating the physical mockups usually becomes expensive, and its fabrication takes a long time. The manufacturer would like to cut these costs and decrease the development period while taking the ergonomic design of the product into consideration.

To cut these costs and to decrease the development period, many 3-D CAD systems have widely spread to the design process of these information appliances. And the 3-D digital mockup of the housing of the appliances can be easily obtained in the early design stage. So there is a strong possibility that we can execute the ergonomic assessments by integrating digital human models, especially including digital hand models, with digital mockups of the appliances to decrease the extra time and cost of making the physical mockups.

Some simulation software using digital human models have been commercialized [2] and are being used in the design of automobiles and airplanes. However, the digital hand models included in these human models of such software do not necessarily comply with the desired accuracy and size variation of human hands when evaluating the relevance of grasping and operating the handheld appliances.

Therefore, our research purpose is to develop a virtual ergonomic assessment system for designing handheld information appliances by integrating the digital hand model with the 3-dimesional product model of the appliance.

As shown in Figure 1, in our system, we realize the following feature functions for ergonomic assessment to satisfy our purpose:

1. Generation of kinematically and geometrically accurate 3-dimensional digital hand models with rich dimensional variation: We apply a digital hand model called "Dhaiba-Hand" [3] to the ergonomic assessment in our system. The Dhaiba-Hand was developed by DHRC, AIST, JAPAN. The Dhaiba-Hand has a very precise hand link structure model which is derived from the kinematic analysis for the measured data obtained from motion capture and MRI[4,5]. 3-D digital hand models with dimensional variation can be generated by deforming a generic hand model which has been created by the factor analysis of dimensional measurements taken from 103 Japanese subjects' hands [3].
2. Automatic generation and evaluation of the grasp posture: By only inputting a few user-interactions, our system automatically generates one of the possible grasp postures determined by the product shape and the digital hand geometry. It also quantitatively evaluates two indices of the grasp: i) *grasp stability* for the product geometry and ii) *ease of grasping* from aspect of finger joint angle configuration. The former i) is calculated based on the *force-closure* and the *grasp quality* used in the grasp planning of robotics. The latter ii) is done based on "ease of grasping evaluation map (EOG-map)" which is constructed from principal component analysis for finger joint angles measured from real subjects' grasps. Moreover, if the finger joint angles of the grasp postures generated in the initial process are inappropriate, the system can correct the finger configuration by executing an optimization method based on genetic algorithm and on the EOG-map.
3. Automatic evaluation of ease of the finger motions in operating the user interface: The system automatically moves fingers of the digital hand by following an operation task model of the user-interface (e.g. which button has to be pushed). It also automatically evaluates ease of finger motions during operation of the user interface based on the flexion joint angles of fingers.
4. Aiding the designers to redesign the housing shapes and to change placement of the physical components of the user-interfaces (e.g. buttons, dials, displays) in the digital mockup: By the above two evaluation indices, the system conducts sensitivity analysis of these indices for some dimensional parameters of the housing. This analysis finds an optimal combination of some dimensional parameters of the housing shapes so as to maximize the evaluation indices for the grasp posture.

In this paper, we mainly describe a part of the above function 2, the evaluation index of ease of grasping and the optimization method of the grasp posture using the EOG-map.

This virtual ergonomic assessment system is being developed as a part of our government-funded project called "Sapporo IT Carrozzeria"[6].

RELATED WORKS

APPLICATION OF DIGITAL HAND IN ROBOTICS, VIRTUAL REALITY AND COMPUTER GRAPHICS

Many researches in robotics, virtual reality (VR) and computer graphics have been proposed in applications for the digital hand model: a grasp planning system for robotic hand design [7,8], a VR environment for directly operating the virtual objects [9], a motion simulator for playing a music instrument [10], or a grasp posture generator for computer animation [11].

However, as described in our previous paper [12], these related works on the digital hand were not necessarily applicable to the ergonomic assessment of handheld information appliances because of the lack of accuracy of the model.

MEASUREMENT AND MODEL CONSTRUCTION OF HUMAN HAND IN ANTHROPOMETRY

In anthropometry, Kouchi [3] developed a generation method of geometrically accurate digital hand models with rich dimensional size variation. These hand models can be generated by deforming a generic hand model which has been created by the factor analysis of dimensional measurements taken from 103 Japanese subjects' hands. Miyata [13] developed a generation method for a precise hand link structure model which is derived from the kinematic analysis for the measured data obtained from motion capture and MRI. These methods are implemented as "Dhaiba-Hand" [3] which is a part of the full-body digital human modeling project "Dhaiba" [14].

GENERATION AND EVALUATION OF GRASP POSTURE

Some research [7,15,16,12,11,17] has proposed the generation and evaluation method of the grasp postures of the digital hand for the objects. As shown in Figure 2(a)(b), the representative approaches for generating the

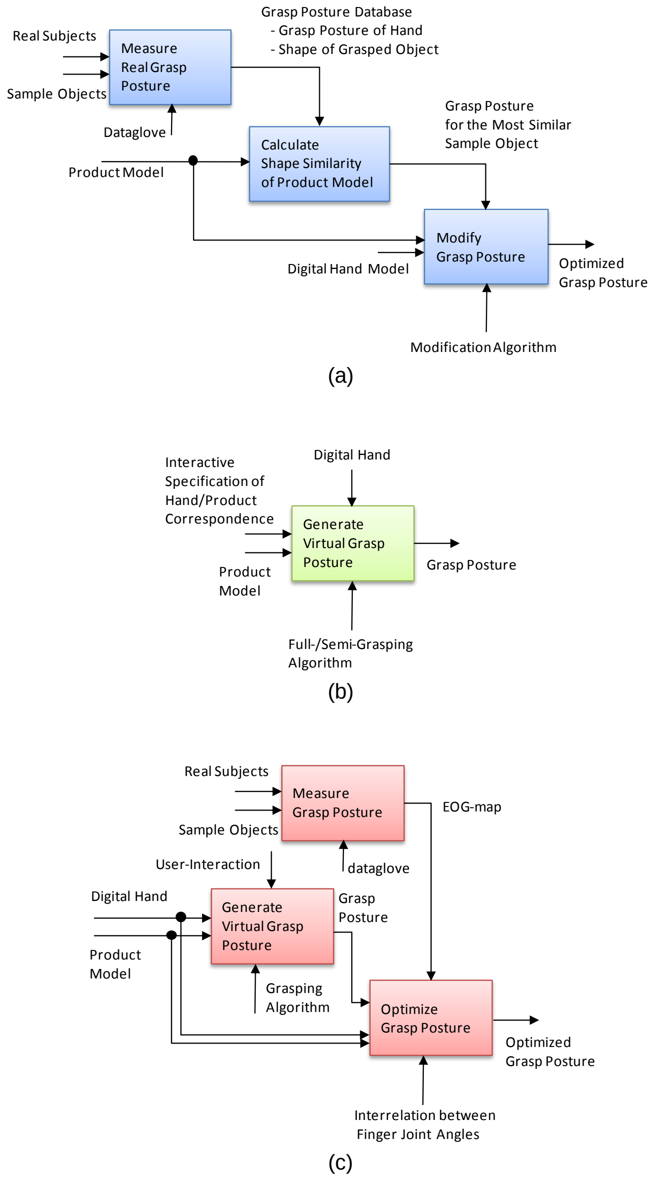


Figure 2. The comparison of the grasp posture generation methods of the related works. (a) A variant method, (b) a generative method and (c) our proposed method.

grasp posture are roughly classified into two types: a variant method [11,17] and a generative method [7,15,12].

In the variant method, the real grasp postures of many subjects for sample objects have been measured in advance using a dataglove to build a grasp posture database. Then, in generations step, one grasp posture whose object shape is most similar to the given object model shape is chosen from the grasp posture database. The selected posture is modified to fit to the product model shape. If the very similar product shape can be found in the database, a nearly appropriate grasp posture for a given product can be obtained after this modification process.

On the other hand, in the generative method, the grasp posture is generated by a full-/semi-automatic grasping algorithm. This method can be executed by the fully automatic algorithm, so it does not need any database of real grasp postures. For any unknown shape, this method can generate a grasp posture that satisfies geometric conditions when the hand is contacting with the product surface.

However, both of these researches did not discuss whether the obtained grasp postures are truly appropriate and possible one or not.

OUR PREVIOUS WORK

DIGITAL HAND MODEL

To perform effective digital ergonomic assessment, it is insufficient to use only one digital hand model with a fixed dimension because the physical dimensions of appliance users differ from person to person. Therefore, we needed to generate a digital hand model with possible anthropometric variation. In this purpose, we used a digital hand model based on the Dhaiba-Hand [3].

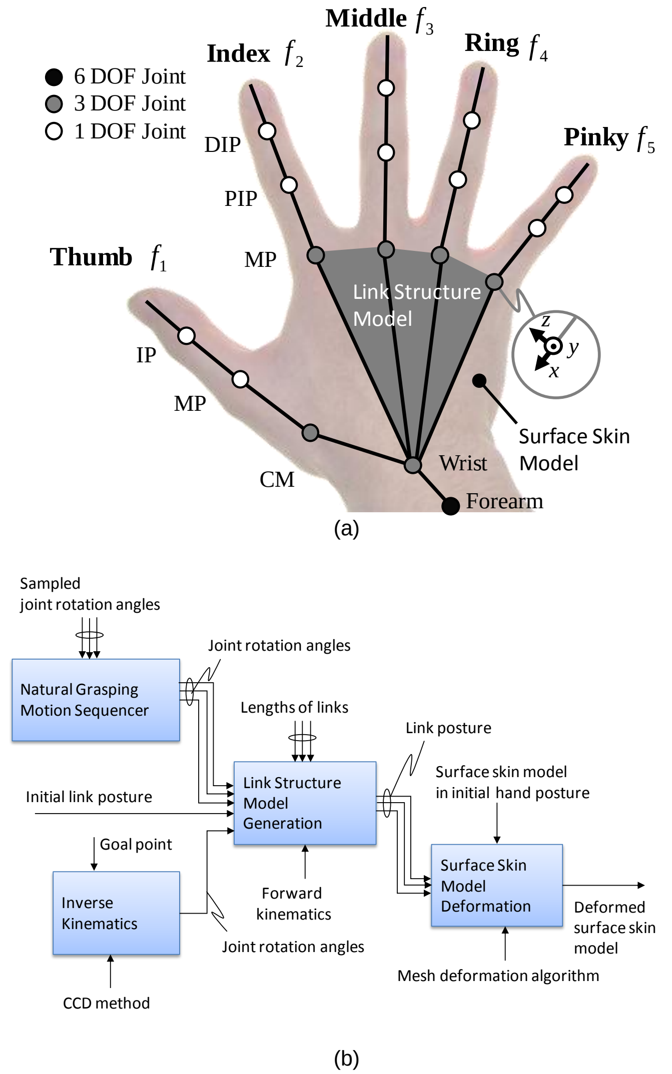


Figure 3. The digital hand model of our system. (a) The link structure model, (b) The flow of the deformation of the surface skin model.

The digital hand model used in our system consists of the following four parts and relation among these parts is shown in Figure 3(b):

1. Link structure model: A link structure model approximates to the rotational motion of bones in the hand. The model was constructed from the measurement by MRI and the motion capture. The model has 17 links, and each link has two joints at both its ends. These joints can rotate with 1, 3 or 6 degrees of freedom, as shown in Figure 3(a).
2. Surface skin model: A surface skin model is a 3-dimensional polygonal mesh for the hand surface generated from CT images, as shown in Figure 3(a). The geometry of the skin model is defined at only one opened posture.
3. Surface skin deformation algorithm: This algorithm defines the deformed geometry of the surface skin model when the posture of the link structure model is changed, as shown in Figure 3(b).
4. Finger closing motion sequencer: The finger closing motion sequencer is a function to automatically and naturally generate a finger-closing motion path of the hand model from a fully opened state to a clenched one, as shown in Figure 3(b). This motion reflects the joint angle constraints of the link structure model.

A link structure and a surface skin model are generated by inputting the 82 dimensional parameters of a specified subject's hand into the *generic hand model* which are implemented in the Dhaiba-Hand [3]. On the other hand, a surface skin deformation algorithm and a finger closing motion sequencer were originally developed by us [12].

GRASP POSTURE GENERATION

The generation of the grasp posture of the digital hand model for the product shape model is the first step in our system. As shown in Figure 4, The process consists of four phases: 1) selection of the contact point candidates, 2) generation of the rough grasp posture, 3) optional correction of the contact points and 4) maximization of the number of the contact points.

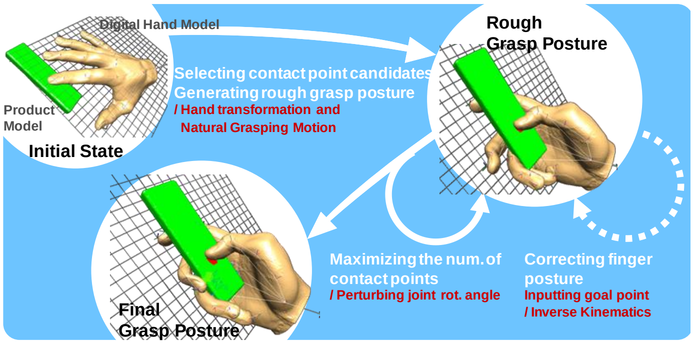
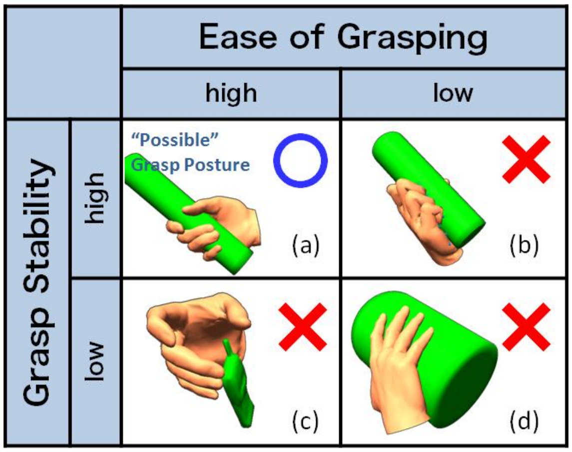


Figure 4. The algorithm to generate the grasp posture.

Table 1. The relation between grasp stability and ease of grasping



		Ease of Grasping	
		high	low
Grasp Stability	high	"Possible" Grasp Posture ○ (a)	✕ (b)
	low	✕ (c)	✕ (d)

EVALUATION OF GRASP STABILITY

After generating the grasp posture, the system automatically evaluates the grasp stability for the product in this estimated posture. We introduced the *force-closure* and the *grasp quality* into the evaluation of the grasp stability.

Originally, in the definition of robotics grasping, a grasp is said to be *force-closure* if it is possible to apply forces and moments at the contact points such that any external force and moments acting on a grasped object can be balanced [18]. Then, a *grasp quality* is defined as "the reciprocal of the sum of magnitudes of contact normal forces required to achieve the worst case wrench" [19].

In our system, the force-closure condition indicates whether the digital hand can grasp the product model stably at the contact points between the digital hand and the product model. Moreover, if an estimated grasp posture can satisfy the force-closure, grasp quality can express how stably we can hold the product at this posture .

We also described the verification results of our system by comparing the estimated grasp postures given from the system with the ones from experiments, and also by comparing the grasp stability evaluated by our system with the ones felt by real subjects.

THE PROBLEMS ON GENERATING GRASP POSTURES AND OUR SOLUTION

As described in the previous section, our generation and evaluation approach for the grasp posture based on grasp stability does not necessarily ensure that the obtained grasp posture is a truly "possible" one. There is a possibility that only using the grasp stability causes the wrong evaluation result. For example, the grasp posture in Table 1(b) satisfies the force-closure and has a high grasp quality value. Therefore, this posture has high grasp stability. But this grasp is not the "possible" grasp posture where the configuration of finger joint angles are quite different from the one we usually take in holding objects. Therefore, we need another index which can evaluate the finger joint angles of the grasp posture. We call this second index “ease of grasping (EOG)”. Of course, only using this index may cause the wrong evaluation results (Table 1(c)) So we define the truly “possible” grasp posture as the one which has a high index value of grasp stability and the ease of grasping, as shown in Table 1(a).

To evaluate the EOG, we have to calculate an index value at a certain configuration of finger joint angles. However, the total degrees of freedom of fingers in a hand ranges from 25 to 32 [20], and it becomes very difficult to calculate an index value from the combination of these many finger angle values.

In neuroscience, some research has found that the finger joint angles of the human hand are strongly interrelated with each other during the grasp motion and at holding state [21]. So the “possible” grasp postures are represented by less variables than the degree of freedom of the hand. Therefore, in this paper, we propose to apply this interrelation of the finger joint angles to decreasing the degrees of freedom of the hand and to constructing a new index for the grasp posture evaluation.

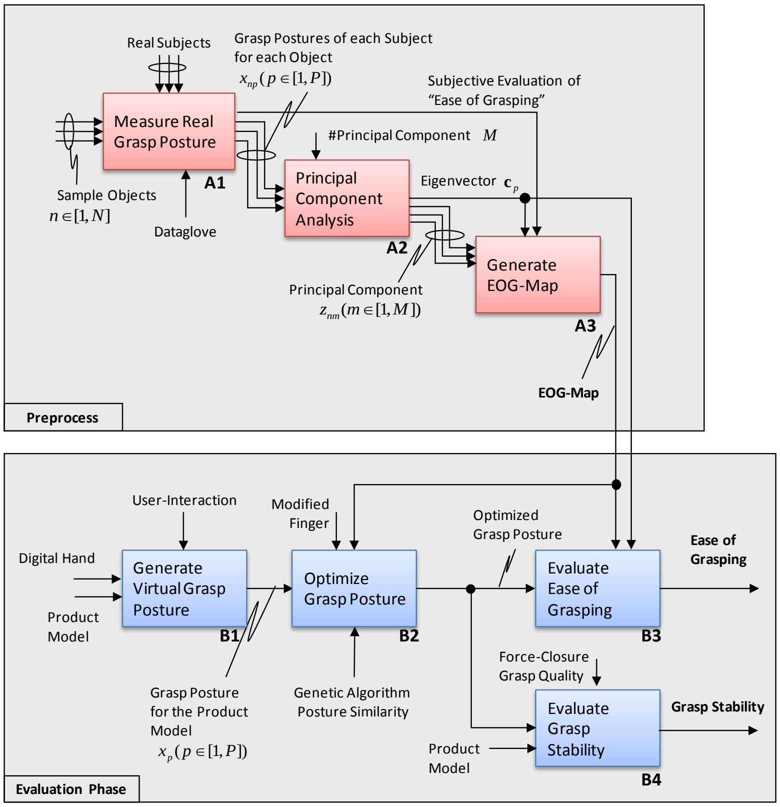


Figure 5. Our proposed system for generation and evaluation fo grasp posture.

THE PROPOSED SYSTEM FOR GENERATION AND EVALUATION OF GRASP POSTURE

In this section, we describe the method of how to evaluate the ease of grasping the object, which is the second evaluation index of the grasp.

FUNCTIONAL OVERVIEW

Figure 6 shows an overview of our evaluation method for the ease of grasping an object in our virtual ergonomic assessment system. The system consists of the following four steps:

1. As a preprocess of the method shown in Figure 5(A1-A3), we construct an “ease of grasping evaluation map (EOG-map)” defined in an *M*-dimensional space, where a large number of actual hand postures from the opened state to the grasping state are plotted.
2. An initial estimated grasp posture is generated for a product model to be grasped (Figure 5(B1)), as described in the process in Figure 4.
3. If the initial estimated grasp posture has an inappropriate finger joint angle configuration, the posture is optimized based on the EOG-map and the genetic algorithm (Figure 5(B2): see the other section).
4. The ease of grasping for the optimized grasp posture is evaluated (Figure 5(B3)).

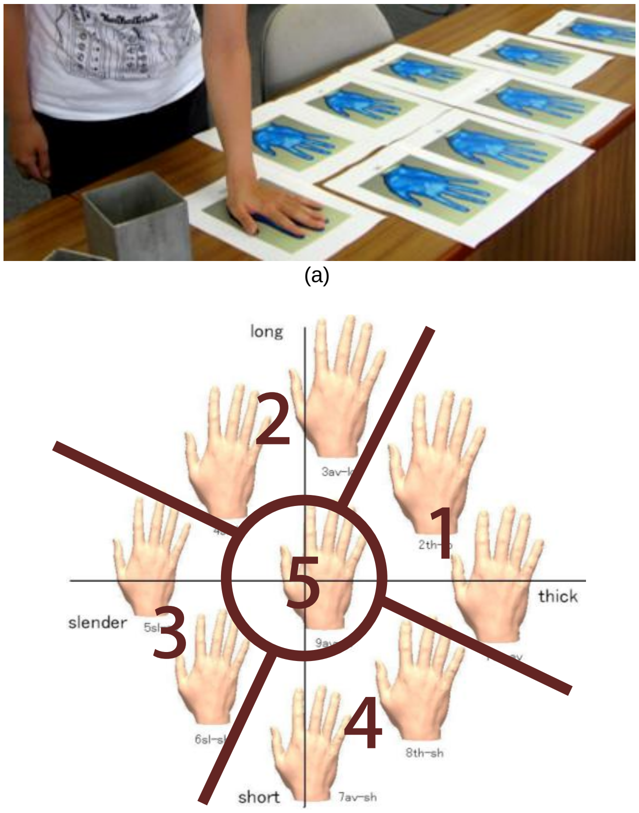
We describe the above 1 and 4 in the following section.

BUILDING THE EOG-MAP

The EOG-map consists of a set of plots in multi dimensional space and each plot corresponds to a finger joint angle configuration measured from real grasping examples. This plot is generated by the following process:

1. For a subject to grasp and an object to be grasped, a sequence of finger joint angles of the subject’s hand from the opened state to the grasping state are measured.
2. A subject is asked to hold a set of objects including primitive shapes and real daily products.
3. A number of subjects are required to carry out the above experimental process of 1 and 2.
4. All recorded sets of finger joint angles are processed by PCA and the results are plotted as points on the EOG-map.

In this map, one posture example is indicated as a set of scores of a principal component analysis (PCA) for the finger joint angles of “real” human hands, measured by a



(a)

(b)

Figure 6. The generation of multiple EOG-map classified by the hand dimension

dataglove. We can estimate the ease of grasping which is generated from a product model and a digital hand by plotting the principal component score for this posture on the map.

PRINCIPAL COMPONENT ANALYSIS FOR FINGER JOINT ANGLES OF HAND POSTURES IN GRASP MOTION

Let's define a set of P joint angles of a hand posture as $\{x_p \mid p = 1,2,...,P\}$. P indicates the degree of freedom of the hand model and is generally defined as more than 30. However, it has been known that finger joint angles are strongly interrelated with each other during the grasp motion [21]. Therefore, we reduce the degree of freedom of the hand posture to less than P by PCA.

Suppose joint angles of the hand postures in grasping for N objects are recorded. We define a set of the standardized measurements of these angles as $\{x_{np} \mid n = 1,2,...,N;\ p = 1,2,...,P\}$, and define a N x P matrix as $X = [x_{np}]$ $(x_{np} \in \Re; n \in [1,N]; p \in [1,P])$. Then we obtain a variance-covariance matrix V and the matrix $W = [w_{ij}]$ $(w_{ij} \in \Re;\ i, j \in \{1,2,...,P\})$ as

$$V = \frac{1}{N-1} X^T X, \qquad (1)$$

$$W = [w_{ij}] = [\,\mathbf{c}_1\ \mathbf{c}_2 \cdots \mathbf{c}_P\,], \qquad (2)$$

where $\mathbf{c}_1, \mathbf{c}_2, ..., \mathbf{c}_P$ are eigenvectors of the matrix V which are sorted in decreasing order of eigenvalue.

Suppose the P finger joint angles can be approximated by M ($M \le P$) principal components, then we approximately describe the hand posture as the first M principal component scores $\mathbf{z}_n = [z_{n1}\, z_{n2} \ldots z_{nM}]$ as follows:

$$z_{nm} = \sum_{p=1}^{P} w_{pm} x_{np} \qquad (m = 1,2,..., M,\ n = 1,2,..., N). \qquad (3)$$

EASE OF GRASPING EVALUATION MAP

Method for Generating the EOG Evaluation Map

By using the above eq. 3, we can evaluate the sequence of the principal component scores z_{nm} of the hand postures from the opened to grasping states for each sample object with "real" subjects. By plotting the first M principal component scores of these postures in a M-dimensional space, we can generate the "ease of grasping evaluation map (EOG-map)". At the same time, we also record the two-level subjective evaluation for the grasp postures (i.e. "easy to grasp / not easy to grasp"). By partitioning the EOG-map into the equally spaced M-dimensional voxel, one of the EOG values is attached to each voxel. The domain of this EOG values can be classified into three categories, which are:

1. EASY TO GRASP — a voxel which includes grasp postures whose subjective evaluations are "easy to grasp"
2. ABLE TO GRASP — a voxel which includes hand postures during the grasping sequence but does not include final grasp postures
3. UNABLE TO GRASP — a voxel which does not include any hand postures

$\mathrm{eog\_vox}(\gamma)$ is defined as

$$\begin{aligned} &\mathrm{eog\_vox} : \Gamma \rightarrow \{easy\_to\_grasp,\ able\_to\_grasp,\\ &\qquad\qquad unable\_to\_grasp\} \qquad (4)\\ &\qquad \Gamma : a\ set\ of\ all\ voxel \end{aligned}$$

Generation of the Multiple EOG-Maps Classified by the Hand Dimension

There is a possibility that a large variance in the hand sizes of the subjects causes different results in the EOG evaluation. To consider this difference, we classify subjects into five groups with respect to their hand dimensions and generate five different EOG-maps for every group. In the experiment for the preprocess, we prepare nine sheets of paper where the nine representative Japanese hands shown in Figure 6(a) are printed. By putting the subject's hand on these sheets, each subject chooses one representative hand that has the most equivalent hand dimension. Based on the class

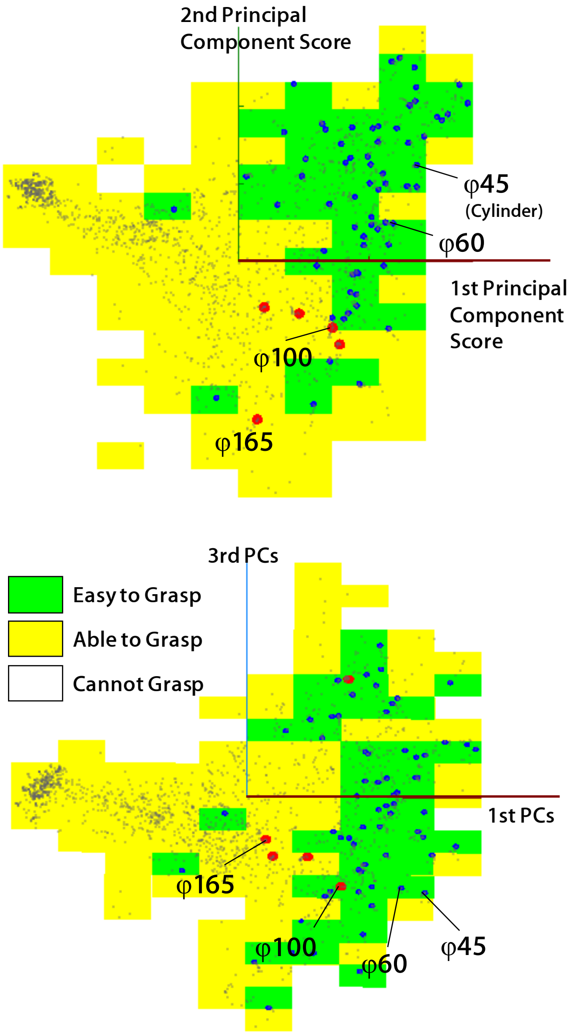


Figure 7. The ease of grasping evaluation map

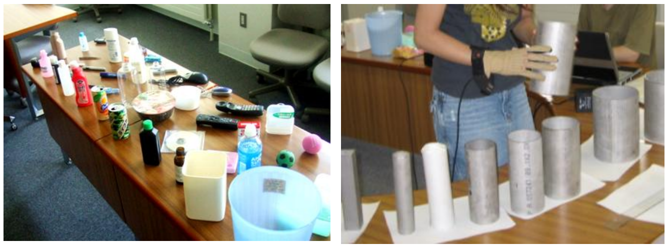


Figure 8. Sample objects used in the test for generating the EOG-map

of their chosen representative hand, the dimensions of the subject's hand are classified into five groups, as shown in Figure 6(b).

Results of Generating the EOG Evaluation Maps

Figure 7 shows one of the EOG evaluation maps generated by the above method (the 5th hand group in Figure 6(b)). The blue/red circular points show the grasp postures that have the subjective evaluation of "easy to grasp / not easy to grasp". The small gray points show the hand postures in grasping sequence. The EOG evaluation maps are generated by 8 subjects and 70 sample objects, as shown in Figure 8. The finger joint angles of this hand postures were measured by the "CyberGlove", which has 19 sensors. We determined that the number M of the principal components should be three, because the cumulative proportion of the first three principal components was more than 80% at every EOG evaluation map of each hand group.

THE EVALUATION AND VERIFICATION FOR EASE OF GRASPING

In the evaluation process in Figure 5(B3), the optimized grasp posture i of the digital hand can be generated. The posture i has the 28 DOF joint angles which is represented as a vector $\mathbf{y}_i^{DH}$. And $\mathbf{y}_i^{DH}$ is converted to a vector $\mathbf{x}_i^{DH} = [x_{i1}, \ldots, x_{i19}]$ defined in the space of the measured joint angles with 19 DOF using a linear transformation. This conversion is done so that some couple of grasp postures for same objects given from the dataglove and the digital hand are identical. The vector of the principal component scores $\mathbf{z}_i^{DH}$ for the digital hand is calculated from $\mathbf{x}_i^{DH}$ using eq. 3. Then, the *ease of grasping* for this grasp posture i $\mathrm{eog}(i)$ can be defined as $\mathrm{eog}(i) = \mathrm{eog\_vox}(\gamma^i)$ where γ^i is a voxel including a point $\mathbf{z}_i^{DH}$, and the function $\mathrm{eog\_vox}(\gamma)$ returns one of the EOG values of the voxel γ as

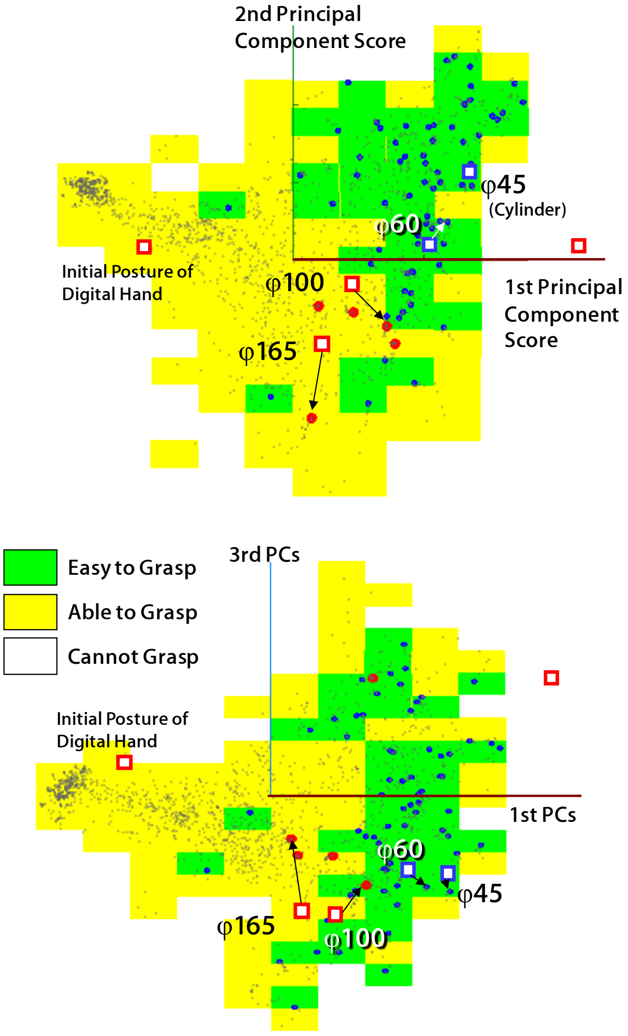


Figure 9. The evaluation and verification results of the ease of grasping

described in the previous section.

We verified the ease of grasping evaluation by plotting some grasp postures of the digital hand on the EOG-map, as shown in Figure 9. These grasp postures are generated from the digital hand and the product models which have the same geometry as the one used in generating the EOG-map. The blue/red rectangle points show the principal component scores of the grasp postures that were estimated as “stable/unstable” grasp posture by force-closure. The two-point pair connected with an arrow shows that these grasp postures are for the same object. The EOG evaluation results produced by taking a digital hand and a real subject’s hand for the same object fell into the same category for almost all cases. Therefore, the proposed EOG-map-based method is effective for evaluating the ease of grasping a product model with a digital hand.

THE GRASP POSTURE OPTIMIZATION BASED ON THE EOG EVALUATION METHOD

OVERVIEW

In some cases, we have an inappropriate finger posture in generating the grasp posture only by the finger closing motion sequencer and maximization the number of the contact points. To modify such a finger posture to the appropriate one, we propose an optimization method for the grasp posture based on the “ease of grasping” evaluation to avoid a particular finger being blocked by the product surface as shown in Figure 10.

First, the system finds one grasp posture as a goal of the modification from the “real” grasp postures that have been measured from subjects and stored in the EOG-map in the previous section. The system finds this goal posture by picking up one posture in the EOG-map which is nearest to the input grasp posture to be modified. This grasp posture can be derived by the similarity of evaluation between two postures described in the following section. Then, the system modifies each finger joint angle to find the appropriate posture where the posture becomes nearest to the goal posture by using the optimization method based on the genetic algorithm.

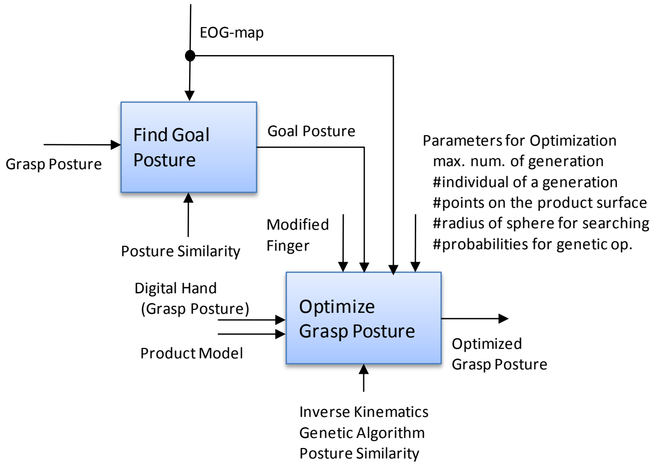


Figure 10. The overview of our proposed optimization for the grasp posture

THE EVALUATION OF THE HAND POSTURE SIMILARITY

We define the *posture similarity* between two hand postures i and j as the L^2 distance between them in the space of the principal component scores (PCs) of the EOG-map as

$$\mathrm{PostureSimilarity}\,(i, j) = \left\| C(\mathbf{z}_i - \mathbf{z}_j) \right\| \qquad (5)$$

where $\mathbf{z}_i, \mathbf{z}_j \in \Re^M$ are the vectors of the PCs of the grasp postures i and j, and C is a M x M matrix

$$C = \begin{bmatrix} w_1 & & & \\ & w_2 & & \\ & & \ddots & \\ & & & w_M \end{bmatrix} \qquad (6)$$

where $w_1, w_2, ..., w_M$ are the cumulative proportions of the principal components. The number of the principal components M is defined as 3.

THE GENETIC ALGORITHM FOR THE GRASP POSTURE OPTIMIZATION

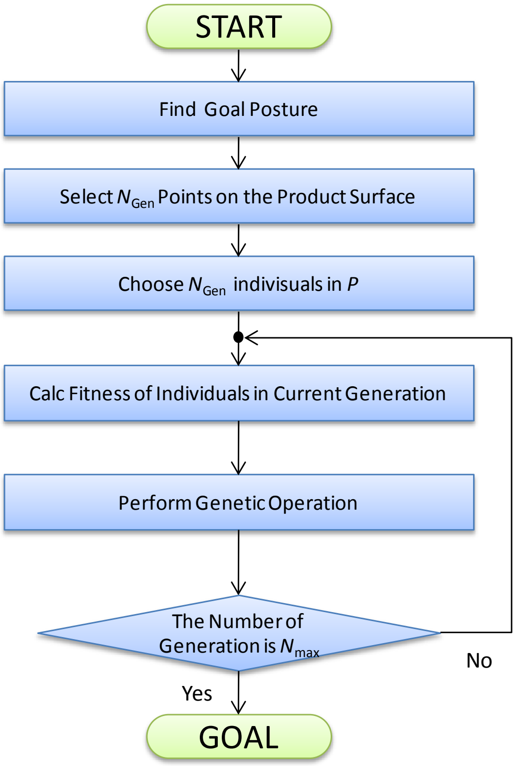


Figure 11. The flow of our method for the grasp posture optimization using the genetic algorithm

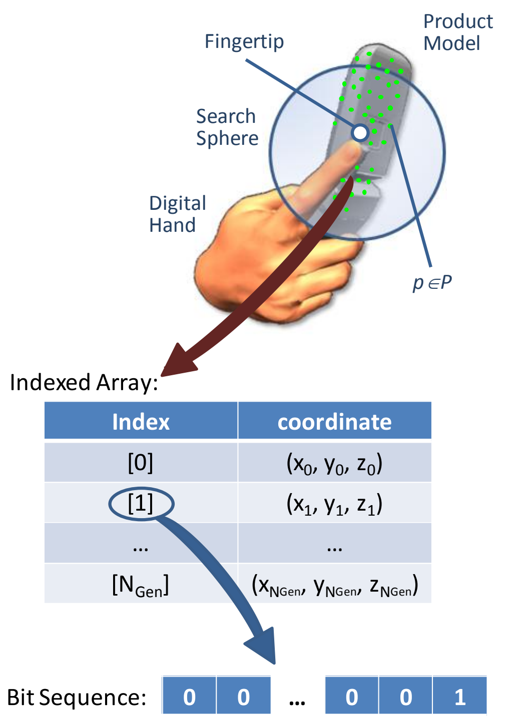


Figure 12. The construction method for the bit sequence of an individual

The objective function for the optimization is based on the posture similarity defined by eq. (5). This function is not differentiable and has the strong possibility of having the local maximums. Moreover, it is quite difficult to evaluate the value of the function for all candidates of the grasp posture, because we have to solve an inverse kinematics problem in every point on the product surface to obtain the grasp posture candidate. Thus we use the genetic algorithm as the optimization method.

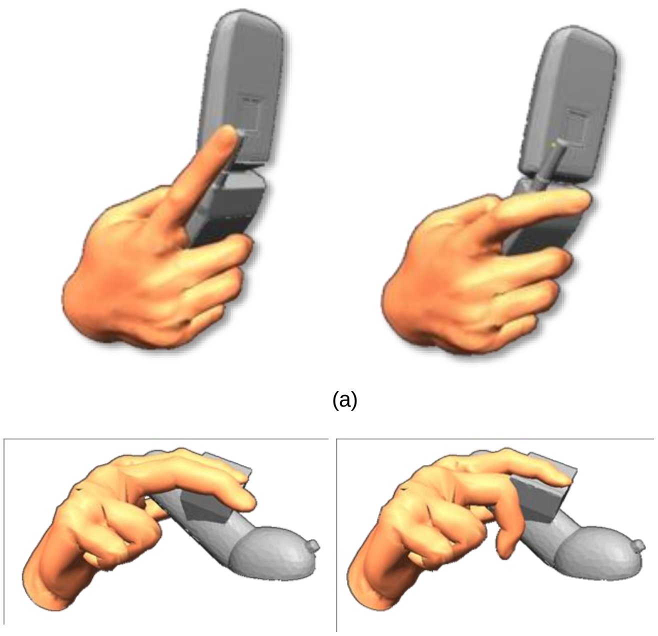
Figure 11 shows the flow of our method for the grasp posture optimization using the genetic algorithm. The algorithm is done as follows:

1. At first, the grasp posture from the digital hand is given as $\mathbf{y}_{Input}$ and is converted to $\mathbf{z}_{Input}$. Then find one goal posture from the “real” grasp postures stored in the EOG-map so that the $\mathrm{PostureSimilarity}(Input, Goal)$ defined by eq. (5) is minimized. The principal component scores of the goal posture is represented as $\mathbf{z}_{Goal}$.
2. As shown in Figure 12, choose a set P of N_{pt} points on the surface of the product model at random. These points are in a sphere whose radius is τ_r and whose center is located at the tip of the finger f_i to be modified. The points in P are sorted in descending order of the x coordinate, then in the y coordinate and in the z coordinate. The result of the sort is stored as an indexed array. An index number of this array is used as a bit sequence of one gene for the following genetic operations.
3. Choose N_{Gen} individuals in P at random, and set them to the individuals in the current generation.
4. Evaluate fitness $\mathrm{Fitness}(p)$ of each individual p in the current generation as described in the following section.
5. Perform the genetic operation (tournament selection, one-point crossover, mutation), and give the birth to offspring.
6. Repeat 4 and 5 N_{Max} times, and output the grasp posture corresponding to the individual which has the highest fitness in the final generation.

EVALUATION METHOD FOR THE FITNESS OF AN INDIVIDUAL IN GENETIC ALGORITHM

In our genetic algorithm, the fitness of an individual is calculated by the posture similarity between the goal posture and the posture generated from the surface points defined by the individual as follows:

1. Calculate the posture of the finger f_i by inverse kinematics so that the fingertip position of f_i is identical to the position of the individual $p \in P$. By using the CCD Method [22], inverse kinematics is solved repeatedly as the following sequences: 1-1) the fingertip position is placed on a set of vertices of the hand mesh belonging to the fingertip portion. 1-2) Calculate the angles θ between the outward normal vector of the fingertip point and the one of the individual p (the point on the product surface). 1-3) Select one finger posture where the θ is nearest to π.
2. Calculate the PCs vector $\mathbf{z}_p$ for the grasp posture whose finger posture of f_i was modified in the first process.
3. Calculate the fitness $\mathrm{Fitness}(p) = 1 / \left\| C(\mathbf{z}_{Goal} - \mathbf{z}_p) \right\|$ for this grasp posture. In case that the digital hand


(a)

(b)

Figure 13. The result of the grasp posture optimization for (a) a cell-phone, (b) a pen-type mouse.

with this posture and the product model is not in state of “CONTACT” described in [12], the fitness is set to 0.

THE RESULTS OF THE GRASP POSTURE OPTIMIZATION

Figure 13 shows two results of our grasp posture optimization for a cell-phone and a pen-type mouse. Modified finger f_i was the index in the cell-phone case and was middle finger in the mouse case. We set the constants to $N_{pt} = 2^{15} = 32768$, $N_{Gen} = 30$, $N_{Max} = 100$. The probability of the tournament selection was set to 0.1, the one of the one-point crossover was set to 0.6. The probability of the mutation at initial generation was set to 1.0, and was decreasing linearly, and one at the final generation was set to 0.0. The processing time was 83s and 25s, respectively. The fitness between the original and the optimized grasp posture were both 15.0. As shown in Figure 13(a), we could find that the index finger position which was blocked by the antenna during closing could move to the appropriate position after applying our optimization method. Also shown in Figure 13(b), the middle finger position which was blocked by the tactile parts during closing could move to the appropriate position after applying our optimization method.

CONCLUSIONS

The conclusions of our research summarizes as follows:

1. We proposed a system of automatic ergonomic assessment for handheld information appliances by integrating the digital hand model with the 3-dimensional product model of the appliances.
2. The EOG-map was generated by the measurement of the grasp postures of real subjects. Based on this map, we proposed an evaluation method for ease of grasping from the product model and the digital hand model. PCA of the finger joint angles enables us to calculate the posture similarity with much less variables than the DOF of the human hand.
3. We proposed an optimization-based method for correcting inappropriate finger configuration by using a genetic algorithm and the EOG evaluation map. The effectiveness of this optimization-based correction was confirmed by examples of the product models of the cell-phone and the pen-type mouse.

In our future research, we will develop a new function to evaluate the ease of finger operation for the use-interface of products, and to aid designers in redesigning housing shapes and user-interfaces in the product model.

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