Optimal Hand Gesture Vocabulary Design Using Psycho-Physiological and Technical Factors

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Abstract

A global approach to hand gesture vocabulary design is proposed which includes human as well as technical design factors. The human centered desires of multiple users are implicitly represented through indices obtained from ergonomic studies representing the psycho-physiological aspects of users. The main technical aspect considered is that of machine recognition of gestures. We review and classify three approaches to this problem: Ad hoc, Rule based, and Analytical. It is believed that this is the first conceptualization of the optimal hand gesture design problem in analytical form. A mathematical dual objective model is developed, which reflects the psycho-physiological and technical performance measures upon which a gesture control system is judged. The mathematical program solves a quadratic assignment problem embedded within a heuristic search tree. The quadratic problem, whose solution is a gesture vocabulary GV, (a command-gesture matching) is solved through simulated annealing. A useful feature, included in the formulation, is the priorities given to the matching of complementary pairs of gestures (say thumb up - thumb down) to complementary pairs of commands (say up - down). To validate the procedure an example is solved for the design of a medium size robot command GV.

Keywords— Hand gesture, optimal vocabulary design, human computer interfaces, multiobjective, metaheurisitic, psycho-physiological, complementary gestures.

1. Introduction

This paper is concerned with one-way communication in which a human commands a machine (or objects on a computer screen) through hand gestures. The machine recognizes and responds to the gesture by carrying out some defined action. The benefits of using gestures to interact with machine devices, such as robots and computers, is that they provide a more natural, expressive, and an intuitive way for humans to communicate. In addition, they provide redundant modalities, overcome noisy environments, are useful in sterile environments, and are particularly suitable for navigational commands. There are two major aspects of human-machine communication through the use of gestures; human based, and machine based. Human based aspects are; fatigue, naturalness, learnability and memorability, while machine-based aspects involve pattern recognition algorithms. Gestures good for one may not be good for the other.

The design of gesture-based interfaces is a virgin area of research. Examination of the literature reveals unstructured approaches. Most research has dealt with the machine aspects of a gesture vocabulary (*GV)*, focusing on recognition algorithms. Current solution methods of *GV* design may be classified as ad-hoc, and rule-based [1], [2], [3]. Ad hoc methods are the prime method of determining a GV whereby an individual constructs the vocabulary, mostly with no rational for the choices made. Few researchers have considered the human psycho-physiological aspects of gesture design. In [4], where human factors are considered, limited attention is given to the technical aspects, with an approach heavy on the human interpretation of rules. Matching of gestures to commands is done empirically through user response queries. In this paper, a new analytical method for *GV* design is proffered, which combines human psycho-physiological and machine based factors.

A global approach that considers the set of all possible hand gestures (an infinite set) is untenable. It is thus necessary to reduce this set to a manageable finite number. Gestures that are difficult to perform, for example gestures that only piano players can perform, are eliminated a priori. The resultant set of candidate gestures is referred to as the master set of size m. Given a predefined set of commands of size n, a GV is determined by selecting a subset of gestures of size n, and pairing them to the set of commands. The number of GVs can be quite large (m!/(n!(m-n)!). Furthermore, once a subset is selected, there are n! possible one to one assignments of gestures to commands. The gestures should be selected in order to meet some performance measures such as; usability, accuracy, robustness, etc. This leads to a formidable problem, which warrants a meta-heuristic solution approach.

In section 2 the basic research problem is defined, along with a mathematical formulation as a multiobjective performance problem. Section 3 contains the proposed methodology to solve the hand *GV* design problem including system architecture and data requirements. In section 4 a medium sized example is solved to validate the methodology. The final section provides conclusions.

2. Problem definition and mathematical formulation

The basic research problem is to provide an analytical method to find an optimal hand *GV*. An optimal hand *GV* is defined as a set of gesture-command pairs that minimize the time for a given user(s) to perform a task(s). Task completion time, as a function of *GV* has no known analytical form. Hence, we use, as proxies, three performance measures; intuitiveness, $Z_1(GV)$, comfort, $Z_2(GV)$, and recognition accuracy, $Z_3(GV)$. The first two are human valued, while the third is machine valued. Intuitiveness of a gesture is the naturalness of expressing a given command. The intuitiveness of a GV is the total of the intuitiveness of each gesture-command pair in the GV. Comfort is inversely related to the stress needed to perform a gesture. Total comfort is equal to the sum of the individual comfort values of the gestures (and gesture transitions) weighed by frequency of use. Recognition accuracy is defined by the percent of gestures successfully recognized by the gesture recognition algorithm.

Maximizing each of the measures over the set of all feasible *GV*s defines a multi-objective decision problem. In [5] this problem is formulated as a three multi-criteria optimization problem, and the frontier of the Pareto [6] solutions is determined through enumeration. Because this enumeration approach is untenable, for even reasonable size vocabularies, we present here a meta-heuristic approach. The approach is applied to a dual objective problem wherein the maximum accuracy objective, and human centered objectives (intuitiveness and comfort) are given as first and second priorities, respectively. If the first priority were human centered, the resultant *GV* may result in low recognition accuracy (because the set of collective gestures may not be successfully discriminated from each other). The dual priority problem is relaxed by considering recognition accuracy as a constraint, and combining the human objective measures into one objective function using a combination of two weights w_1 , and w_2 .

Problem P_1: Relaxed problem

$$Max\ \bar{Z}(GV) = w_1 Z_1(GV) + w_2 Z_2(GV) \tag{1}$$

$$GV \in \Gamma$$

$$s.t.\quad Z_3(GV) \geq A_{\min} \tag{2}$$

The minimal acceptable accuracy is $A_{\min}$,, determined by the decision maker, and Γ is the set of all GVs.

2.1 Two stage decomposition procedure

Determination of recognition accuracy depends only on on the subset of gestures, G_n (it does not depend on the matched command-gesture pairs in the gesture vocabulary, *GV)*. Thus, it is possible to use a decomposition approach whereby the first stage is to find a feasible solution that satisfies (2). In a second stage, this feasible solution is substituted in (1), and solved for the optimal *GV*. The first stage problem, P_2, is that of finding a gesture subset G_n from the set of all possible G_n s that satisfies a given minimal accuracy $A_{\min}$.

2.1.1 Problem P_2: Stage 1 (feasible subset selection)

Find G_n such that:

$$A(G_n) \geq A_{\min} \tag{3}$$

$$G_n \subseteq G_m, n \leq m \tag{4}$$

Because the accuracy function is unknown, the search for a feasible solution to P_2 is found through the use of a metaheuristic described later in this paper. Denote the feasible solution found from P_2 as G_n*. For simplicity, and when understood, G_n* is represented by the set of indices {0,1,..i,..,n}, where i represents the i^{th} gesture type in the feasible subset.

Once G_n* is found, the second stage is initiated. Using G_n* the relaxed problem can be formulated as a quadratic 0-1 integer assignment problem (QAP) [7]. Define sets of weighted comfort and weighted intuitive indices u_{ijkl} and (v_{ij}, v_{ijkl}), respectively. A useful feature, included in the formulation, is the priorities given to the matching of complementary pairs of gestures (say thumb up - thumb down) to complementary pairs of commands (say up - down). The details of determining the above indices are described subsequently. Let P_3 be the 0-1 integer QAP problem with binary assignment variables x_{ij} equal to 1 if command i is assigned to gesture j, and zero otherwise.

2.1.2 Problem P_3: Stage 2 (QAP)

$$max\ \bar{Z}(G_n^*) = w_2 \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} u_{ijkl} x_{ik} x_{jl} + w_1\left[\sum_{i}^{n}\sum_{j}^{n} v_{ij} x_{ij} + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{l=1}^{n} v_{ijkl} x_{ik} x_{jl}\right] \tag{5}$$

$$s.t.\quad \sum_{j=1}^{n} x_{ij} = 1, \quad i = 1,..,n, \tag{6}$$

$$\sum_{i=1}^{n} x_{ij} = 1, \quad j = 1,...,n, \tag{7}$$

$$x_{ij} \in \{0,1\}, \quad i = 1,...,n, \quad j = 1,...,n, \tag{8}$$

The objective equation (5) (see (1)) represents the weighted sum of the comfort and intuitive objectives. The first term represents the comfort of the pair of assignments (i,k) and (j,l) (assigning command i to gesture k and command j to gesture l). Maximizing the first term tends to pair high frequency use commands with less stressful gestures. The need for the quadruple subscripts is due to the need to include the stress of transitions between non-identical gestures k and l. The second term represents the intuitiveness (weighted by frequency of use) v_{ij}, of an assignment (i,j). Higher values of v_{ij} force more intuitive gesture-command pairings. The third term represents the intuitiveness (weighted by frequency of use) of matching complementary commands (i,j) to complementary gestures (k,l). Higher values of the complementary intuitive indices, v_{ijkl} will force solutions in which complementary command–gesture pairs are matched. Constraints (6) and (7) ensure that each command i is paired with exactly one gesture, and each gesture j is paired with exactly one command, respectively. To solve the 0-1 integer QAP a simulated annealing approach such as that described in [8] is used. The solution to P_3 provides a set of n assignments $\{x^0_{ij} = 1\}$. This is converted to a $GV=\{(i, p(i) \mid i=1,..,n)$ where, p(i)=j indicates command i is assigned to gesture j.

3. Methodology

The proposed methodology is developed under the assumptions that; (a) gestures are static postures, (b) each gesture cannot represent more than one command, and each command must be expressed by exactly one gesture, (c) the human psycho-physiological factors are represented as fatigue (comfort) and intuitiveness indices and are available from empirical experiments, (d) the recognition accuracy of a subset of gestures is determined by a fuzzy means classifier (or any other recognition algorithms), and (e) the minimal acceptable recognition accuracy is provided by the system designer. The optimal hand GV architecture (Fig. 1) consists of: (a) determination of the human psycho-physiological input factors, (b) Stage 1- a gesture subset search subject to machine gesture recognition accuracy, and (c) Stage 2 - a command - gesture matching.

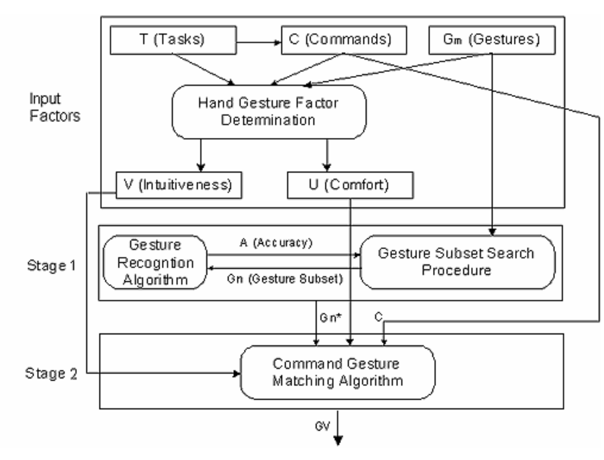

Figure 1. Architecture of hand GV methodology

The task set(s) T, command set for each task, and master gesture set G_m are exogenous inputs. Given a set of tasks, the union of all commands used to perform all tasks constitutes C. More details and methods for estimating these factors appear below. The inputs to Stage 1 are the matrices; intuitiveness V, comfort U, gesture G_m, and a recognition algorithm to determine A. This stage employs an iterative search procedure to find the best gesture subset G_n*, for a given accuracy level. A disruptive confusion matrix (DCM) method is developed to conduct the search. In Stage 2 the subset of gestures G_n* from Stage 1 is matched with the set of given commands C, such that the human measures are maximized. The resulting gesture-command assignment constitutes the *GV*.

3.1 Hand gesture factor determination.

In this section the inputs to the two stage decomposition procedure are described including the methods taken to compose the U and V matrices. In addition, the algorithm to determine the recognition accuracy A is described.

3.1.1 Task and command sets (T, C). The task set T, is single or multiple element set. The tasks are those to be conducted through gesture commands for a domain specific application. For each task t_i , a set of C_i commands are defined. For a multi-task set $T=\{t_1,..,t_n\}$, the command set is the common commands, $C = \bigcup_{i=1,,n} C_i$.

3.1.2 Command transition matrix (F). To estimate the frequency of command usage for the set of tasks, it is necessary to perform experiments using a real or virtual model of the application. For a command set C of size n, a matrix F_{nxn} is constructed, where f_{ij} represents the frequency that a command c_j is evoked, given that the last command was c_i. This measure is significant in the sense that it is hypothesized that; (a) an optimal hand gesture vocabulary will pair high frequency commands to gestures that are most comfortable to perform (low fatigue); and (b) the physical ease of movement between gestures will be paired with high frequency command transitions.

3.1.3 Master gesture set (G_m). Since the set of all possible gestures is infinite, we first establish a set of plausible gesture configurations. To create the set of all plausible hand pose gestures, there are two possible approaches; (a) visual capture of gesture images, or (b) creation of synthetic gestures. For small hand gesture databases, real hand gestures images may be captured and labelled with configuration parameters that characterize the gestures; For large gesture sets (thousands of gestures) a tedious effort is required, which may be overcome by the use of a synthetic (virtual) gesture generator. One possible way is to generate the configurations by specifying a number of primitives such as; finger positions (extended, spread), palm orientations (up, down sideways), etc. For additional material on gesture primitives, and combining them into whole gestures, including those for dynamic gestures see [9]. The master list, however, should be pre-perused to eliminate gestures that are awkward to perform (for example, gestures only performed by piano players).

3.1.4 Matrices of intuitive indices (I, IC, V). The intuitive index is a measure of how "natural" it is for a user to express a command with a particular gesture. These indices are determined empirically. For each command c_i a user is queried to select or display the gesture that he/she "cognitively" associates with the command. Using this information it is straightforward to construct an intuitiveness matrix, $I_{n \times m}$. The entries of I are represented as a_{ik}. and are determined by:

$$a_{ik} = n_{ik} / N_i \quad , i = 1,\ldots,n \quad , \quad k = 1,\ldots,m \tag{9}$$

Where, n_{ik} is the number of users that select gesture g_k to express command c_i, and N_i is the number of trials for the i^{th} command. Note, that the values of a_{ik} lie between 0 and 1. For a given command c_i, gestures with larger values of a_{ik} represent more intuitive associations. Gesture-command pairs that do not meet a minimum threshold for intuitiveness (e.g. point up for a scroll down command) can be eliminated by setting the associated a_{ik} to zero.

An exceptional case is that of complementary (opposite) commands and gestures. Complementary gestures may be created by palm flips, finger flexing and wrist pans. Examples of complementary commands are; left-right, fast-slow. It is more intuitive to associate a pair of complementary commands with a pair of complementary gestures, such as; up-down with thumb up–thumb down. We represent the naturalness of matching a pair of complementary commands (i,j) with a pair of complementary gestures (k,l), by a complementary intuitive index of the form a_{ijkl} . Higher values of complementary intuitive indices will have the effect of forcing complementary pairings. The matrix of complementary intuitive indices $IC_{nm \times nm}$, can be quite large, but can be compacted since most of the entries will be zero. The intuitive and complementary intuitive indices are weighted by frequency of use, to obtain $v_{ij} = f_{ii}a_{ij}$, and $v_{ijkl} = f_{ij}\, a_{ijkl}$, respectively. We denote V as the appropriate matrix for the weighted intuitiveness indices.

3.1.5 Fatigue and comfort matrices (S, $\bar{S}$,U). The fatigue (or its inverse comfort) indices are determined through an experiment which displays a biomechanical model of the hand to assist in the empirical collection of physical fatigue measures [10]. The results are arranged in a matrix $S_{m \times m}$, whose common element s_{ij} represents the physical difficulty of performing a transition from gesture i to gesture j. The comfort matrix $\bar{S}$ is achieved by applying an inverting function to each element. Let the coefficients u_{ijkl} be the entries of a total comfort matrix $U_{nm \times nm}$, An entry $u_{ijkl} = f_{ij} \times \bar{S}_{kl}$ represents the frequency of transition between commands i to j times the comfort of a k to l transition when commands i and j are paired with gestures k and l, respectively in a given *GV*. This product reflects the concept that the total comfort measure of a *GV* depends on the frequency of use of a gesture (or gesture pair transition). Note, that the diagonal terms represent the total comfort of using a gesture repeatedly to carry out the same command.

3.1.6 Gesture recognition algorithm, A. An important part of the *GV* search procedure is the determination of recognition accuracy for each G_n examined. The recognition process consists of: (a) extracting relevant features from the raw image of a gesture, and (b) using those image features as inputs to a classifier. Such an algorithm is described in [11], where the segmentation consists of the extraction of the hand gestures from the background using greyscale cues. The captured hand image is thresholded to a black/white segmented hand silhouette, and partitioned into block features. Using a distance metric, these features are compared to clusters obtained from a trained fuzzy c-means clustering algorithm. The classification results are organized as a confusion matrix which allows the recognition accuracy to be computed using (10).

$$Z_3(GV) = \frac{(\text{total gestures} - \text{gestures misclassified})}{\text{total gestures}} 100 \tag{10}$$

Training the classifier is repeated many times for different candidate G_ns. The parameters for the classifier must also be recalibrated. Since gesture classifiers such as a neural network, boosting method, etc. require large training sets, the gesture recognition algorithm selected is a fast FCM classifier which requires a relatively small training set. An automated method, based on an evolutionary parameter search procedure, is used to train and recalibrate the recognition algorithm every time it is called, providing a seamless operation (see [12], [13]).

3.2 Stage 1:(Gesture subset search procedure)

Consider a subset solution G_n that has a recognition accuracy below the minimum desired value. One notes that the indices of the gestures have no meaning. Thus, given a subset solution, G_n, and its neighbourhood solutions obtained by some gesture exchange rule, there is no physical reason that the $A(G_n)$ function is well behaved within this neighbourhood. Hence, attempting to find a local max by the standard search methods of gradient ascent will fail. This leads to a metaheuristic approach for solving P_2. This approach is referred to as the Disruptive Confusion Matrix (DCM) method wherein pairs of gestures are exchanged and maintained in a binary tree. Each of the most confused gestures in the subset is discarded, and replaced by a gesture in the master set using a maxmin rule. The maxmin rule selects a gesture from the master set that is least similar (farthest away) from all the gestures in G_{n-1} (i) (where i is the gesture removed from the current subset). Like simulated annealing, the method allows moves towards the direction of inferior solutions possibly avoiding pre-convergence to local optima. This method generates a sequence of gesture subsets until one is found which satisfies the desired recognition accuracy. This feasible solution is then used in the gesture-command matching problem P_3 to obtain *GV**.

3.2.1 Initial subset construction. The root node of the search tree corresponds to the initial G_n selected from the master set G_m. This requires the construction of a square matrix D with common element $d_{ij} = d(\bar{g}_i, \bar{g}_j)$, where $\bar{g}_i, \bar{g}_j$ are the prototype vectors of gesture type i, j, respectively. This prototype vector is obtained by finding the centroid of the feature vectors of the training set of the gesture type. The similarity measure d_{ij} is the Euclidean distance between the vectors $\bar{g}_i$ and $\bar{g}_j$. (the smaller d_{ij} the more similar the gestures). Finding the initial G_n is based on the maxmin inter-gesture distance and is solved by removing the closest pair of gestures in G_m until the number of gestures remaining is n. The remaining gestures constitute the initial subset G_n^0

3.2.2 $A(G_n)$: Accuracy of the set of gestures, G_n. Once a new subset of gestures G_n is obtained, its accuracy, $A(G_n)$, is determined by calling the recognition algorithm. When removing one gesture and replacing it by a new one the dynamics of the clustering obtained by the FCM classifier is changed. Thus, the FCM classifier must be retrained and recalibrated. The result of the training session is a confusion matrix, which is used to determine most confused pair of gestures, and subsequently the branching of the search tree.

3.3 Stage2: (Command-gesture matching)

In this stage the feasible gesture G_n* found from the DCM procedure is matched to commands, using P_3, to obtain the final *GV*.

4. Example problem

The method is validated using a medium size example of twelve gestures, and eight commands.

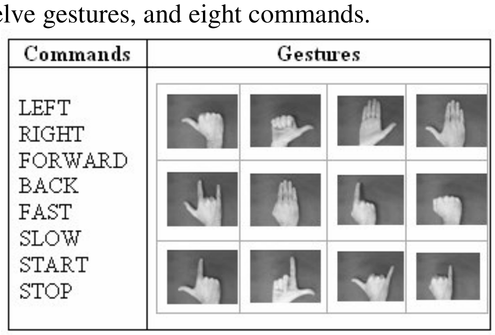

Figure 2. Hand gesture vocabulary

Since gestures have no name labels associated with them, they are represented as gesture types g_0, g_1,g_2,..,g_i,.. g_{11} indexed row wise from top to bottom in figure 2. The number of gesture subsets of size 8 is 495. Since a *GV* has 8! possible matchings, the solution space is ~ $20\text{x}10^6$. The command-command transition frequencies are obtained by a car-maze navigation experiment repeated seven times. The totals of each command transition recorded in the matrix F_{nxn}. The intuitive indices are the collective subjective assessments obtained from subject queries. Stress indices for individual gestures and movements between them are obtained by subjective estimates with the aid of a hand biomechanics study [10]. In addition, twelve complementary intuitiveness indices a_{ijkl} are set to 100 for complementary command pairs (i,j) = (0,1), (2,3), (4,5), (6,7); and complementary gesture pairs (k,l)= (0,1), (2,3), (8,9) representing (left, right), (forward, back), (fast, slow), (start, stop); and (g_o, g_1), (g_2, g_3), (g_8, g_9), respectively. All other a_{ijkl} are set to zero. Complementary gestures are obtained by palm flips. Thirty images of each gesture type, collected from six subjects, are used to train the recognition algorithm.

The initial solution G_n^0 = [0,1,2,5,6,7,9,11] is found by the maxmin method. The solution tree is shown in Fig. 3. New nodes that correspond to previously generated solutions are terminated. Such nodes can be identified in the graph by "cyclic arcs" which emanate from them and connect to previous generated nodes at the same or higher level (for example (10 and 7), (15 and 11)).

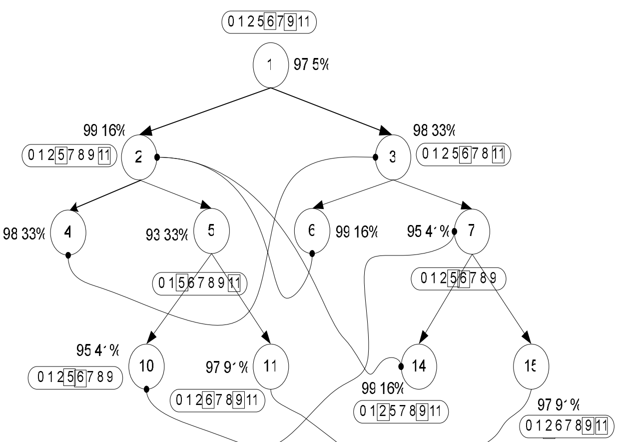

Figure 3. Improvement tree for the example

The best solution found is G_n* = [0,1,2,5,7,8,9,11] at node 14 with 99.16 percent accuracy. Five unique subsets were examined out of a possible 495 constituting only one percent of the solution space. The best-matched commands for G_n* are shown in Fig. 4. Note, the two complementary gesture pairs, which appear in G_n*, are matched with two of the complementary command pairs. The complementary command pair (start, stop) was not selected for matching to a complementary gesture pair, because in task they are used only once, and hence had low complementary intuitive indices.

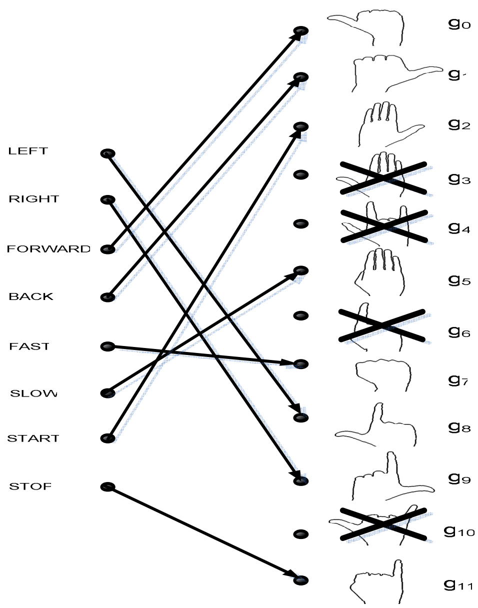

Figure 4. Command-gesture matching

5. Conclusion

In this research a rigorous formulation and solution methodology to the *GV* design problem is proffered. Two aspects drive the need for such a method; *GV* design research is presently an ad-hoc procedure, and gesture interfaces can provide more natural intuitive communication with non-human devices such as computers and robots. Of the three design methods, ad-hoc, rule-based and analytical, we believe this is the first conceptualization of the optimal hand *GV* design problem in analytical form. The objective is to first maximize gesture recognition accuracy and second to maximize human centered factors (intuitiveness and comfort).This dual priority problem is solved by a meta-heuristic using a two stage decomposition approach. In the first stage, a gesture subset is selected from a master set of gestures which satisfies a minimum acceptable accuracy level. Here a disruptive confusion matrix method is developed to create the branches of a search tree. To address the problem of repeated training of the gesture recognition system for each candidate subset of gestures in the tree an automated parameter calibration is employed. In the second stage a QAP assigns gestures to commands such that the human centered measures are optimized. A numerical example is solved to validate the procedure. The methodology requires an effort to obtain human ergonomic and cognitive indices. This effort allows the construction of a gesture knowledge database for subsequent studies and updating. Comparisons to previous work are difficult as no analytical approaches were found in the literature. Future work includes explicit modelling of the trade off between usability and accuracy.

6. Acknowledgement

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7. References

[1] T. Baudel,. and Beaudouin-Lafon, “Charade: Remote Control of Objects using FreeHand Gestures”, *Communications of the ACM*, vol. 36, no. 7, , 1993, pp. 28-35.

[2] R. Kjeldsen and J. Hartman, “Design Issues for Vision-based Computer Interaction Systems”, in *Proc. of the Workshop on Perceptual User Interfaces*. Orlando, Florida, USA, 2001.

[3] K. Abe, H. Saito, and S. Ozawa, “Virtual 3-D Interface System via Hand Motion Recognition from Two Cameras”, *IEEE Trans. Systems, Man and Cybernetics, Part A*, vol. 32, no. 4, Jul. 2002, , pp. 536-540.

[4] M. Nielsen, M. Storring, T. B. Moeslund, and E. Granum, “A Procedure for Developing Intuitive and Ergonomic Gesture Interfaces for Man-Machine Interaction”, Technical Report CVMT 03-01, CVMT, Aalborg University, March, 2003.

[5]] H. I. Stern, J. P. Wachs and Y. Edan, “Hand Gesture Vocabulary Design: A Multicriteria Optimization”, IEEE SMC 2004, International Conference on Systems, Man and Cybernetics, The Hague, Netherlands, Oct 10-13 2004

[6] K. V. Pareto. Manuel, D' Economie Politique. Marcel Giard, Paris, 2nd Edition, 1927.

[7] T. C. Koopmans, and M. J. Beckmann, “Assignment Problems and Location of Economic Activities”, *Econometrica*, no. 25, 1957, pp. 53-76.

[8] D. T. Connolly, “An Improved Annealing Scheme for the QAP”, European Journal of Operational Research, no. 46, 1990, pp. 93-100.

[9] B. W. Miners, O. A. Basir, and M. Kamel, “Knowledge-Based Disambiguation of Hand Gestures”, Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Volume 5, October 6-9, 2002, pp 201-206.

[10] R. Natan, H. Stern and J. Wachs (supervisors), Fourth Year Project , D. Bardenstein, and T. Ben-Yair, Depart. Of Mech. Engr, Ben Gurion University, Israel, 2003.

[11] J. P. Wachs, H. Stern, Y. Edan, “Real-Time Hand Gesture Telerobotic System Using the Fuzzy C-Means Clustering Algorithm”, *WAC 2002*, Orlando, Florida, U.S.A, vol. 13, , 2002, pp. 403 – 409.

[12] H. Stern, J. Wachs, and Y. Edan, ”Parameter Calibration for Reconfiguration of A Hand Gesture Tele-Robotic Control System”, Japan-USA Symposium on Flexible Automation, Denver, CO July 19 - 21, 2004.

[13]] J. P. Wachs, H. Stern and Y. Edan, “Cluster Labeling and Parameter Estimation for Automated Set Up of a Hand gesture Recognition System”, *IEEE Trans. Systems, Man and Cybernetics, Part A*, vol. 35, no. 6, Nov., 2005, pp. 932-944.