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A Search Method in Knowledge-Based Systems using Euclidean Space Norm - An Application to Design of Robot Grippers.

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Abstract

This paper presents a search method that uses non-deterministic knowledge. The method uses the mathematical concept of Normed Spaces, and particularly, a subset of the n-dimensional Euclidean space with norm. The norm determines whether a feasible solution could be transformed to a final solution of the problem or not. The main characteristics of this method are the fast search of the feasible solutions, qualitative and quantitative assignments of the solutions and the increase of the flexibility of the knowledge-based system. The quantitative assignment is achieved by using the Euclidean norm, and the qualitative one by using limits of the state space based on norms. An application of this method in a knowledge-based system is presented for the conceptual design of grippers for handling fabrics with robots.

1 Introduction

According to Rich & Knight[1], every search method can be viewed as a traversal of a tree structure in which each node represents a problem state and each arc represents a relationship between two states. There are two basic search algorithms:

- Depth-first search.

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- Breadth-first search.

A heuristic is a technique that improves the efficiency of a search method, possibly sacrificing claims of completeness[1]. Some well-established heuristic techniques are the next:

- Generate-and-test.
- Hill climbing
- Best-first search.
- Problem reduction.
- Constraint satisfaction.
- Means-ends analysis.

These techniques are called weak methods, because when applied to a particular problem, their efficacy is highly dependent on the way they exploit domain-specific knowledge. In addition, all the heuristic techniques are dependent on the quality of the heuristic function, which maps from problem state descriptions to measures of desirability, usually represented as numbers. The main reason, which makes all these methods useless by their own, is that they can deal only with single tasked problems.

The above techniques are commonly used with knowledge-based systems. Heuristic search methods using fuzzy numbers are used for the representation of the evaluation of the problem state[2]. De Mathelin, et.al.[3], use Bayesian estimation theory and fuzzy logic in order to derive knowledge combination rules for heuristic search algorithms.

German & Germanovich[4] presented a system for solving problems based on the concept of integration of weak methods of searching for a solution and non-algorithmic programming methods. Stewart[5] develops a heuristic search algorithm that determines the non-dominated set of solution graphs for a multiobjective AND/OR graph. This algorithm uses sets of vector-valued heuristic estimates to give guidance to the search.

According to Kainz & Kaindl[6], the static evaluation functions of heuristic search algorithms are those that make use of the knowledge applied to the given state but not result generally in the state space- neither the search guided by the evaluation nor extra search like look-ahead. The authors propose a new approach that utilizes differences of known costs and their heuristic functions from a given evaluation to improve other heuristic estimates from this function (dynamic evaluation function).

Perneel, et.al.[7], used the fuzzy logic theory in order to build a specific decision-making system for heuristic search algorithms. Two optimization methods were created, by the usage of genetic algorithms and neural networks, to improve the systems approach.

In this paper, a new search method is presented. It is a combination of an exhaustive search method and of a heuristic function to find the set that contains final solutions of the problem. The heuristic function is the Euclidean norm. It determines whether a feasible solution could be transformed to a final solution of the problem or not. First, the set of feasible solutions for each hypothesis is defined, by using an exhaustive method. Next, the heuristic method is fired in order to find all the final solutions to the set of hypotheses by combination or not of the feasible ones. An application of this method in the development of a knowledge-based system is presented for the conceptual design of grippers for handling fabrics with robots. An extended example of the expert system is, also, included.

2 Heuristic method analysis

The problem under consideration has multiple hypotheses. This means that all the hypotheses must be fulfilled simultaneously by one or a combination of general ideas, called conclusions that incorporate confidence degrees. Problems like this are very common. For example, what should be the combination of medicines in a patient, which suffers from the effects of a curious disease? Another example from the field of engineering, in order to justify the need of the development of this method, is the conceptualization of grippers for handling fabrics. In the early 80s, the apparel industry started importing robots in product lines. The first grippers manufactured were made for particular jobs, for example, separation of a ply from a stack. During the last years, grippers are able to accomplish more than one job, e. g. separation, placing or assembling, but not always successfully.

The rules of a knowledge-based system may be of the form:

If *hypothesis* Then *conclusion* $< c \in [0,1] >$.

where,

c: degree of confidence.

For example,

If hypothesis no. 1 Then conclusion no.1 $< c_{11} >$;
conclusion no.2 $< c_{12} >$

According to the above general rule form, in a problem with multiple hypotheses a matrix with the degrees of confidences between the hypotheses and conclusions will be produced. Each column- in this matrix- represents a certain combination of conclusions, and consists a feasible solution to the problem under consideration. The matrix has the form of table 1.

Table 1: Degrees of confidence of conclusions in connection with hypothesis.

	Conclusion (C) No.			
Hypothesis No.	1	2	…	m
1	c_{11}	c_{12}	…	c_{1m}
2	c_{21}	c_{22}	…	c_{2m}
⋮	⋮	⋮	⋱	⋮
n	c_{n1}	c_{n2}	…	c_{nm}

In table 1, $c_{ij} \in A$, where $A \subset \Re : A = [0,1]$,
and, i=1,…, n, j=1,…,m.

The columns of the matrix can be considered as vectors $\vec{C_i}$ in the space $V = A^n$. A measure of this space can be the norm $\|\cdot\|$, which is defined for a vector $\vec{u} = (x_1, x_2, ..., x_n)$ as, [8]:

$$\|u\| = \left(\sum_{i=1}^{n} |x_i|^2 \right)^{1/2} \tag{1}$$

The norm in this case can be considered as the heuristic function. The norm has, always, positive real values. The maximum norm in the space V corresponds to the vector $\vec{E_n}$, which has all its elements equal to 1:

$$\left\|\vec{E_n}\right\| = \|(1,1,...,1)\| = \sqrt{n} \tag{2}$$

The norm shows how close is a vector to $\vec{E_n}$, which has the biggest norm, and is the best solution to the problem.

Qualitative assignments, from the range of values "good", "medium" and "bad" can be made to the vectors. For this purpose three rules are used:

1. If $\left\|\overrightarrow{C_i}\right\| \geq \ell_1$ Then vector $\overrightarrow{C_i}$ is "good";
2. If $\ell_2 < \left\|\overrightarrow{C_i}\right\| < \ell_1$ Then vector $\overrightarrow{C_i}$ is "medium";
3. If $\left\|\overrightarrow{C_i}\right\| \leq \ell_2$ Then vector $\overrightarrow{C_i}$ is "bad".

where, $\overrightarrow{C_i}$ is an n-dimensional vector. The limits ℓ_1 and ℓ_2, may get the next values:

$$\ell_1 = f_1\left\|\overrightarrow{E_{n-1}}\right\|, \text{and } \ell_2 = f_2\left\|\overrightarrow{E_{n-1}}\right\|, \tag{3}$$

define two spheroids in the n-dimensional space, $\sigma(\vec{0}, \ell_1)$ and $\sigma(\vec{0}, \ell_2)$, respectively[16]. As a consequence the rules can be written as:

1. If $\overrightarrow{C_i} \in A^n - \sigma(\vec{0}, \ell_1)$ Then $\overrightarrow{C_i}$ is "good".
2. If $\overrightarrow{C_i} \in (\sigma(\vec{0}, \ell_1) - \sigma(\vec{0}, \ell_2)) \cap A^n$ Then $\overrightarrow{C_i}$ is "medium".
3. If $\overrightarrow{C_i} \in \sigma(\vec{0}, \ell_2) \cap A^n$ Then $\overrightarrow{C_i}$ is "bad".

The regions which are defined by these rules are illustrated for a two dimensional problem in fig.1. As solutions of the problem are considered all the vectors to which a "good" value has been assigned. It is presumed that the vectors in the matrix are sorted from the left to the right by their norm value.

The f_i, i=1,2 are factors which are defined by the designer and specify how strict are the criteria for the selection of final solutions. These factors may get the following values:

$$f_1 \in \left(1, \frac{\left\|\overrightarrow{E_n}\right\|}{\left\|\overrightarrow{E_{n-1}}\right\|}\right], \quad f_2 \in [0,1] \tag{4}$$

The f_1 factor ensures that the vectors do not have zero values. A vector with at least one zero value in this method is a partial solution (with assignment "bad" or "medium") of the problem. This justifies the lower bound of this factor. For example, consider a three dimensional problem with a feasible solution (1,1,0). This vector has the same norm with the vector $\overrightarrow{E_2}$, which is the best solution in another problem (2-dimensional problem). So, the vector (1,1,0) cannot be assigned as "good". The upper bound strictly defines the "good" vectors as those, which are the same with $\overrightarrow{E_n}$.

The f_2 factor plays a regulating role. It stops the algorithm when it searches for final solutions in case that only "bad" vectors are left.

The limits ℓ_i, i=1,2 need a slight modification in the case of one-dimensional problem. These limits take values in the bounds:

$$\begin{aligned} \ell_1 &\in (a,1], \\ \ell_2 &\in [0,a] \end{aligned} \tag{4}$$

where $a \in (0,1)$.

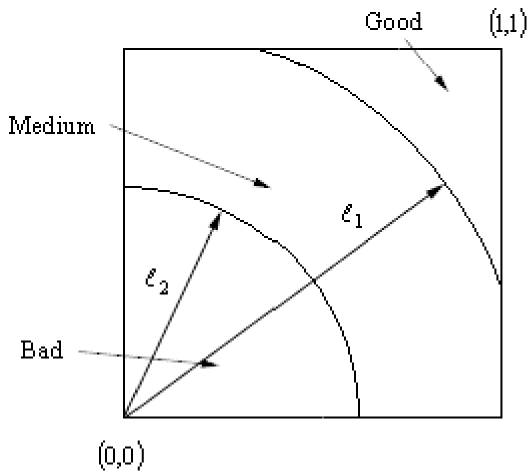

Figure 1: Regions of qualitative and quantitative assignments.

For example, in fig.1, if $f_1 = \frac{\left\|\vec{E}_2\right\|}{\left\|\vec{E}_1\right\|}$, then the only vectors with value equal to "good" are those that reach the point (1,1). If $f_2 = 0$, then, only the vectors (0,0) are considered as "bad".

In some cases, new solutions can be obtained by combination of preexisting feasible solutions. The new final solution ($\overrightarrow{NC}$), using feasible solutions $\overrightarrow{C_i}$, can be created as follows (assuming that the vectors having the biggest norm are sorted from the left to the right):

$$\overrightarrow{NC}(k) = \max_{k=1,\ldots,\dim\left(\overrightarrow{C_1}\right)} \left(c_{kj}, c_{k(j+1)}, \ldots, c_{kn}\right) \qquad (5)$$

where, the j-th vector has "medium" norm.

The natural mean of that is that, when the j-th vector cannot match a particular hypothesis, some other will. If the new vector $\overrightarrow{NC}$ is not affected by $\overrightarrow{C_{j+1}}$, then the vector $\overrightarrow{C_{j+1}}$ is rejected and the method continues up to the last column. The new conclusion, to be considered as solution, must satisfy the first rule otherwise it is rejected and the method stops for the particular vector $\overrightarrow{C_j}$. However, the algorithm continues until the vector $\overrightarrow{C_j}$ gets a "bad" assignment and the method stops.

The above method was tested in MATLAB 5.1 and implemented in Kappa P. C. 2.3.2 for a knowledge-based system for the design of grippers for handling non-rigid materials.

3 An illustrative example

A knowledge-based system for the design of grippers for handling non-rigid materials was used as an application. As it was mentioned before, there exist a lot of concepts for grippers, which are used in apparel industry. These grippers were, initially, constructed for implementing particular jobs. The current trend is to manufacture grippers, which under the same concept, may accomplish different tasks. The existing grippers, that provided knowledge for generating the knowledge base, do not present the same efficiency for different tasks (Dlaboha[9], Eiichi, et. al.[10], Kemp, et. al.[11], Monkman & Shimmin[12]; Paraschidis, et. al.[13], Taylor[14]).

In order to make the conceptualization of grippers easier two knowledge-based systems were developed. A conventional one and one based on the present approach. More information about the knowledge acquisition and the development of the conventional knowledge-based system can be found in Moulianitis, et. al.[15].

The basic features of the two systems are:

- Conceptualization of the gripper, the control strategy, the sensing requirements and the auxiliary equipment.
- Determination of final solutions.
- Determination of optimum solution according to a number of criteria. (This is possible by applying specific criteria emerging from the knowledge available for the current case).

More specific, the conventional knowledge-based system uses four criteria to determine the optimum solution (maintenance, reliability, repeatability and, cycle time). The current knowledge–based system uses five. The extra criterion is the normalized norm. These criteria are weighted by the designer. In addition, the current knowledge-based system has the ability of multilevel presentation of the solutions something that is meaningless for the conventional one.

In the following, a multitasked problem is presented as an example. The same inputs are used in both systems:
Required Task: Separation-Placing of a fabric material.
Status of Material: Free (free from above and free from the edge).

By starting a new reasoning the designer is asked to input more data. Assume- for the present case- that this data are:
Material's identity: Cotton
Material's thickness: 0.4 mm
Material's porosity: 20%
Material's surface: Smooth
Material's density: High
Material's molecular weight: High
Material's weight: High
Material's texture: Knitted
Material's status of fibers: Clinged
Environment: Dust

According to the above data, the current knowledge-based system produces eight feasible (fig. 2, table 2) and seven final solutions, (fig. 3, table 3). The coefficients of limits that are used in order to obtain the feasible solutions are $f_1 = 1$ and $f_2 = 0.3$. A final solution is considered one that its value of confidence is "good". A feasible solution could be a final one, as can be seen from fig. 2.

The first two feasible solutions (adhesive and vacuum) are final solutions to the problem. The next feasible solutions are assigned as "medium".

They must be combined with each other in order to upgrade their values. The method starts with the feasible solution no. 3 (clamp). It compares it with the next feasible solution (freezing). As it can be shown in table 2, the feasible solution no. 4 is redundant for no. 3, so it is excluded. All the feasible solutions from no. 4 to no. 7 are redundant for no. 3. When the method reaches solution no. 8, a new vector is constructed with values:

$$\overrightarrow{NC_1}(k) = \max_{k=1,2}\left(\overrightarrow{C_3}(k), \overrightarrow{C_8}(k)\right) \Rightarrow \overrightarrow{NC_1} = (1, 0.6) \quad (6)$$

This vector has "good" assignment, so it is a final solution. The method continues with feasible solution no. 4 and goes on. When it reaches feasible solution no. 8 it stops because there isn't any other to be combined. All the final solutions are shown in table 3. If a feasible solution had a "bad" assignment, when the search method reached it the algorithm would be stopped. It is meaningless to search for good solutions in a set of bad solutions.

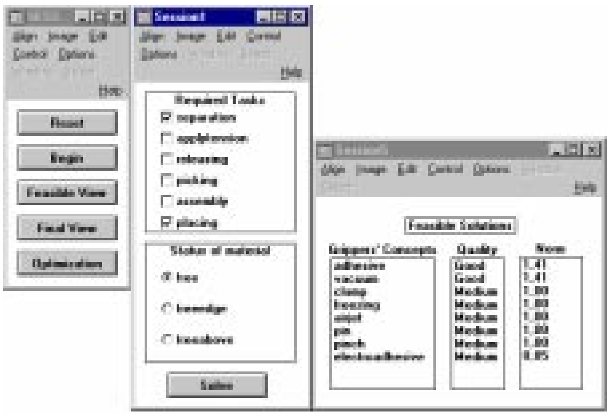

Figure 2: Feasible solutions.

The optimum solution can be found by using the five criteria, as it is mentioned above. An optimization technique was used with the weight coefficients given below and the results are shown in fig. 4:

- Maintenance: 0.5;
- Reliability: 1;
- Repeatability: 0.8;
- Cycle time: 0.6;
- Normalized Norm of Degree of Confidence: 1;

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Table 2: Certainty values of feasible solutions.

		Separation	Placing
1.	Adhesive	1	1
2.	Vacuum	1	1
3.	Clamp	1	0
4.	Freezing	1	0
5.	Airjet	1	0
6.	Pin	1	0
7.	Pinch	1	0
8.	Electroadhesive	0.6	0.6

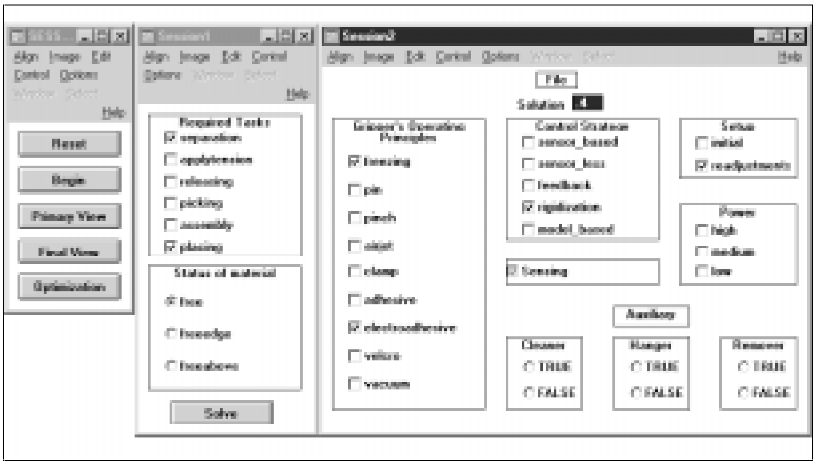

Figure 3: Final solution no. 4 of the design problem.

Table 3: Final solutions.

	Final Solutions	
1.	Adhesive	
2.	Vacuum	
3.	Clamp	Electroadhesive
4.	Freezing	Electroadhesive
5.	Airjet	Electroadhesive
6.	Pin	Electroadhesive
7.	Pinch	Electroadhesive

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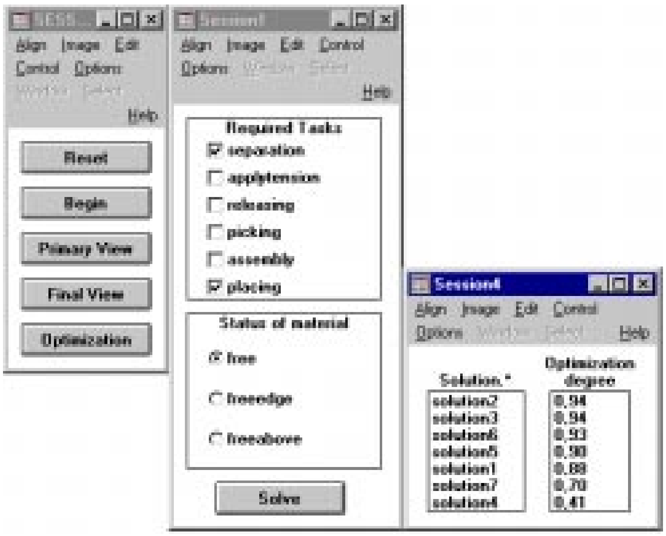

Figure 4: Optimization degree of the final solutions.

The conventional knowledge-based system would give only two solutions with feasible concepts, namely, adhesive and vacuum and no combinations would be achieved. So, the problem could be solved partially.

3.1 Discussion of results.

In the above example, the quality of the first two feasible solutions (fig. 2) is considered as “good”. So, these two solutions are final solutions of our problem. The other five final solutions were created by combination of the feasible solutions, which are not “good”. The optimum decision depends on the priority of the five criteria that are defined by the designer (fig. 4).

As it can be seen in fig. 3, the solution is a multigripper, which, as far as it is known it doesn’t exist commercially. So, for that case, some original design is needed. As an alternative, either two robots each one with its own gripper, can be used or one robot equipped with a magazine providing the proper gripper to the robot.

Compared with the previous version of the knowledge-based system, which could give only two feasible, non-final solutions, the current knowledge-based system proves to be more flexible. In the latter, interactions occur between the designer and the proposed system in this particular and critical point. If the number of the final solutions isn't enough, the designer can increase the region of the accepted final solutions using the f_i, i=1,2 factors and vice versa.

4 Conclusions.

In this paper, a search method for a knowledge-based system is presented. The method uses the theory of Euclidean Space with norm. The method works in multiple hypothesis problems as well as in single one problems with slight modifications. It combines qualitative and quantitative representation of solutions in order to make the interaction with the designer compliant. In addition, it is more flexible since the designer can change the limits that define the solutions. The norm that the method uses can be used to formulate a criterion for further selection of the optimal solution of the problem something that doesn't exists in the conventional knowledge-based system. The advantages of the proposed method may contribute towards more reliable knowledge-based systems, especially in the field of design.

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