PROBABILISTIC WORKPSACE SCAN MODES OF A ROBOT MANIPULATOR COMMANDED BY EEG SIGNALS

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Abstract: In this paper, probabilistic-based workspace scan modes of a robot manipulator are presented. The scan modes are governed by a Brain Computer Interface (BCI) based on Event Related Potentials (Synchronization and Desynchronization events). The user is capable to select a specific position at the robot's workspace, which should be reached by the manipulator. The robot workspace is divided into cells. Each cell has a probability value associated to it. Once the robot reaches a cell, its probability value is updated. The mode the scans are made is determined by the probability of all cells at the workspace. The updating process is governed by a recursive Bayes algorithm. A performance comparison between a sequential scan mode and the ones proposed here is presented. Mathematical derivations and experimental results are also shown in this paper.

1 INTRODUCTION

Brain Computer Interfaces have got a great impulse during the last few years. The main reasons for this growing are the availability of powerful low-cost computers, advances in Neurosciences and the great number of people devoted to provide better life conditions to those with disabilities. These interfaces are very important as an augmentative communication and as a control channel to people with disorders like amyotrophic lateral sclerosis (ALS), brain stroke, cerebral palsy, and spinal cord injury (Kubler et al.,2001, Wolpaw et al., 2002).

The main point of a BCI is that the operator is capable to generate commands using his/her EEG (electroencephalographic) signals in order to accomplish some specific actions (Wolpaw et al., 2002, Lehtonen, 2003, Felzel, 2001, Millán et al., 2003). Thus, an operator using a BCI can control, for example, a manipulator, a mobile robot or a wheelchair (amongst other devices) without using any muscle. The EEG frequency bands have enough information to build an alphabet of commands in order to control/command some kind of electronic device (Ochoa, 2002). In this paper a BCI, which is controlled through alpha waves from the human brain, is used. Although the EEG signal acquisition/conditioning, which is part of this BCI, was developed in other work of the authors (Ferreira et al., 2006), one of the objectives of this paper is to illustrate its versatility, mainly in terms of the simple algorithms used.

Event related potentials (ERP) in alpha frequency band are used here. Such potentials are ERD (Event Related Desynchronization) and ERS (Event Related Synchronization), well described in the following sections. This BCI has a Finite State Machine (FSM) which was tested in a group of 25 people.

The main contributions of this paper are the scan mode algorithms proposed to allow the user to command a manipulator (Bosch SR-800), based on a probabilistic scan of the robot's workspace. The workspace is divided into cells. Each cell contains three values: its position (x, y) at the robot's workspace plane and a probability value. This value indicates the accessibility of that element. Once a particular cell is accessed, its probability is updated based on Bayes' rule.

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This paper is organized as follows: a brief description of the sequential scan mode of the manipulator's workspace is presented in section 2. The probabilistic scan modes proposed are shown in Section 3. Section 4 shows the results for a Montecarlo experimentation, where the probabilistic evolution of the whole workspace and of a specific cell is presented. Section 5 shows the conclusions of this work.

2 SEQUENTIAL SCAN MODE

As a brief introduction, the sequential scan mode of the robot workspace developed in Ferreira et al. (2006) is presented here.

The workspace is previously divided into three main zones as it can be seen in Fig. 1. The system iteratively scans from *zone 1* to *zone 3* until one of them is selected by the user (using EEG signals). Once it is so, the selected zone is scanned row by row until one is selected. Once a row is selected, the system scans cell by cell (switching columns) iteratively inside the selected row. After a cell is selected by the user, the robot reaches the position given by that cell.

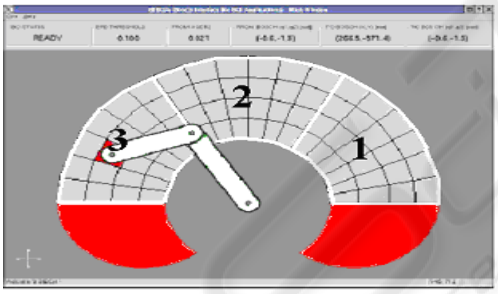

Figure 1: Main zone division at robot's workspace.

3 PROBABILISTIC SCAN MODES

The two probabilistic scan modes shown in this paper are based on Bayes rule for updating probability values of the cells at the manipulator's workspace. The scan modes are shown in the following sections.

3.1 First Approach of a Probabilistic Scan Mode

The first approach of a probabilistic scan mode works as follows:

1. The workspace's resolution is set to 72 cells and can be easily changed, decreasing or increasing this number. The workspace behaves as a *pmd* (probabilistic mass distribution).
2. Each cell has its own initial probability. This value can be previously determined by some heuristic method (for example: if the BCI operator is right-handed, then cells to the right of the workspace will have higher accessing probability than the ones to the left). However, it is also possible to set all cells to a probability near zero, in order to increase or decrease them depending on the times they are accessed by the user. In this work, the first case was adopted.
3. Let *a* and *b* be the higher and lower probabilities cells respectively. Then, the workspace is divided into three zones according to these values. Table 1 shows how division is made. Let $P(C_i \mid G)$ be the probability of cell C_i given a group G to which it belongs.
4. Every zone at the workspace is divided in three sub-zones under the same philosophy presented before. Each one of these sub-zones contains a set of probabilistic weighted cells.
5. The scan mode proceeds as follows:
   I. First, the zone with the highest probability value at the workspace is highlighted. If that zone is not selected by the operator, the second highest probabilistic zone is highlighted. If it is not selected, the highlight passes to the third and last zone. The scan keeps this routine until a zone is selected.
   II. When a zone is selected, the highlight shows first the sub-zone with the highest probability inside the zone previously selected. The scan, in this case, is exactly the same used in the last step.
   III. When a sub-zone is selected, then the scan highlights first the cell with the highest probability of occupancy. If it is not selected, the scan passes to the next cell value. This routine keeps going on until a cell is selected. Once a position is selected, the probability value of the cell, sub-zone, zone and complete workspace is updated. The update of the probabilities values is made by the Bayes' rule.

As it can be seen, the number of cells that belong to a sub-zone or a zone is variable. Then, the organization of the zones at robot's workspace is dynamic. This allows improving the scan mode in order to access in a priority way to the most frequently used cells.

The probability update of each cell at the workspace is based on the recursive Bayes' rule. Once a cell is reached by the user, its probability value changes according to (1).

Table 1: Workspace's Zones Definitions.

a	highest probability cell value
b	lowest probability cell value
$\left\{c_i : b+\frac{2}{3}(a-b) < P(C_i \mid G) \le a\right\}$	zone 1: the set of all cells which probabilities are the highest of the workspace
$\left\{c_i : (b+\frac{(a-b)}{3}) < P(C_i \mid G) \le \le (b+\frac{2}{3}(a-b))\right\}$	zone 2: the set of all cells which probabilities are of middle range
$\left\{c_i : b \le P(C_i \mid G) \le (b+\frac{(a-b)}{3})\right\}$	zone 3: the set of all cells with the lower probability of the workspace.

Let C be any cell at robot's workspace and G a set to which that cell belongs. Thus, the updating algorithm is given by,

$$P_k(C \mid G) = \frac{P_k(G \mid C)P_{k-1}(C \mid G)}{P_k(G \mid C)P_{k-1}(C \mid G) + P_k(G \mid \overline{C})P_{k-1}(\overline{C} \mid G)} \quad (1)$$

Though (1) is mainly used in very simple applications (Thrun et al., 2005), it fits as an updating rule for the purpose of this work.

Equation (3) can be re-written in (4), where a scale factor was used.

$$P_k(C \mid G) = \eta P_k(G \mid C)P_{k-1}(C \mid G) \quad (2)$$

According to the Total Probability Theorem (Thrun et al., 2005), η is the scale factor, which represents the total probability of $P(G)$. In (1), $P_{k-1}(C \mid G)$ is the prior probability of a cell given the primary set to which it belongs at time $k-1$. $P_k(G \mid C)$ is the transition probability which represents the probability that a given cell C belong to a set G. Finally, $P_k(C \mid G)$ is the posterior probability -at instant *k*- of the cell used given the zone to which it belongs.

In order to make sense to the use of the recursive Bayes algorithm, an initial probability value must be given to all cells at the workspace.

Figure 2 shows the evolution of a cell's probability when it is accessed successively by the user.

The cell used in Fig. 2, for example, has an initial value of 0.05 but it is increased each time the cell is accessed by the user. As was expected, the maximum value a cell can reach is one. When this situation occurs, the whole workspace is scaled. This scaling does not change the scan mode because the relative probability information remains without changes, i.e., if a cell *p* has the maximum probability over all cells, after scaling, *p* will continue being the cell with the highest weight. A more extended development of this algorithm can be seen at Papoulis (1980). Once the updating algorithm is complete, the scan algorithm is released as described in Section 3.

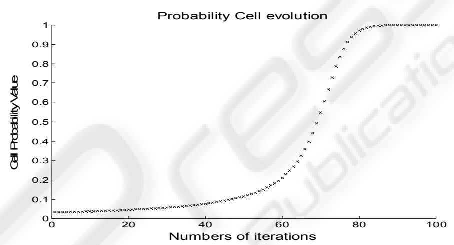

Figure 2: Evolution of Cell's probability when successively accessed.

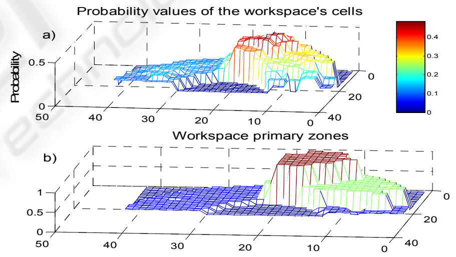

Figure 3: Probabilistic distribution of a workspace for a right-handed user.

Figure 3 shows the workspace's *pmd* for a right-handed user. Fig. 3.a shows the cells probability's value and Fig. 3.b shows the different zones of the manipulator's workspace.

3.2 Second Approach

This second approach investigated in this work is based on the sequential scan mode algorithm. Each zone or sub-zone -as those shown in Fig. 1- has a probability value associated with it. As the workspace is considered as *pmd* then each zone or sub-zone's probability value is calculated as the sum of all probability values of the cells that belong to that group. The scan mode proceeds as follows:

1. The zone with the highest probability is highlighted first; then, the second higher

probability zone is highlighted and then the last zone (see Fig. 1). The highlighting process repeats until the user chooses a zone.

2. Once a zone is chosen, the row with the highest probability -inside that zone- is highlighted. A row of a zone is known as sub-zone. If this sub-zone is not selected by the user after a period of time, the highlight passes to the next higher probability value row. This process is repeated iteratively until a row is selected by the user.
3. Once a sub-zone is chosen, the cell with the highest probability of that sub-zone is highlighted. If it is not chosen after a period of time, the highlight passes to the next higher probability cell. The process continues and if no cell is chosen, it starts from the beginning cell.
4. If a cell is chosen, then its probability is updated according to the Bayes rule (Eq. 3). Then, workspace *pmf*, sub-zone's probabilities and all zone's probabilities are also updated.

The sampling time used in all scan modes is the same one used in Ferreira et al. (2006).

4 EXPERIMENTAL RESULTS

This section is entirely dedicated to compare the three scan types: sequential and probabilistic ones. For this purpose, a Montecarlo experiment was designed (Ljung, 1987). This experiment shows the performance of the three methods by measuring the time needed to reach different cells at the robot's workspace.

4.1 Montecarlo Experiment

The robot's workspace consists of 72 cells. It also can be considered as a 4×18 matrix. According to this, a cell's position is defined by a number of row and a number of column at that matrix. The number of a row and a column can be considered as a random variable. To generate a random position of a cell destination, the following algorithm was implemented.

i. An uniform random source generates two random variables: x and y.
ii. The random variable x is mapped into the rows of the 4×18 matrix workspace.
iii. The random variable y is mapped into the columns of the 4×18 matrix workspace.
iv. When a position is generated, both scan types begin. The time needed to reach the cell is recorded.
v. After the system reaches the position proposed, a next process point generation is settled -the algorithm returns to point i-.

4.2 Mapping Functions

Let f_x be a mapping function such as:

$$f_x : A \to B$$
$$x \to m$$

where,

$$\begin{cases} A = \{x : x \in [0,1) \subset \Re\} \\ B = \{m : m \in \{1,2,3,4\} \subset \aleph\} \end{cases} \tag{3}$$

and let f_y be another mapping function such as:

$$f_y : A \to C$$
$$y \to n$$

where,

$$\begin{cases} A = \{y : y \in [0,1) \subset \Re\} \\ B = \{n : n \in \{1,2,3,...,18\} \subset \aleph\} \end{cases} \tag{4}$$

Equations (3) and (4) show the domain and range of the mapping functions. Finally, the mapping is made according to the following statements.

i. Let δ be the sum of all weights at robot's workspace, that is, $\delta = \sum_{i \in B} \sum_{j \in C} P_{ij}$, where P_{ij} is the probability value of a cell located at the $i-row$ and $j-column$.
ii. Let $x \in A$ be an outcome of the uniform random source for f_x.
   - If $0 \le x < \frac{\sum_{i=1, j \in C} P_{ij}}{\delta}$ then $f_x(x) = i = 1$. This means that the value of $x \in A$ should be lower than the sum of all cell's values in row one -over δ - to $f_x(x)$ be equal to one.
   - If $\frac{\sum_{i=1, j \in C} P_{ij}}{\delta} \le x < \frac{\sum_{i=2, j \in C} P_{ij}}{\delta}$ then $f_x(x) = i = 2$. This means that $x \in A$ should be greater or equal to the sum of all cell's values in row one and lower than the sum of all cell's values in row 2.
   - The same process continues up to the last row, whose expression is: if $\frac{\sum_{i=3, j \in C} P_{ij}}{\delta} \le x < \frac{\sum_{i=4, j \in C} P_{ij}}{\delta}$ then $f_x(x) = i = 4$.
   - Each time a cell is selected, the mapping functions vary. It is so because they are

dependent with the probability value of the cells.

- For the mapping over the columns, the procedure is the same, however in this case, the sum is made over the set B (four rows).

Concluding, the mapping presented here is dynamic because it is updated each time a cell varies its probability value. For the case implemented in this work (a right-handed user) the initial mapping functions are represented in Figs. 4.a and 4.b. In Fig. 4.b is also possible to see that column 10 has higher probability than column 1. It is also important to see that, if all cells at robot's workspace have the same probability weight, then the mapping functions would be uniform. Thus, each row or column would have the same probability to be generated.

4.3 Montecarlo Simulation Results

The objective of Montecarlo experiments was to test the performance of both scanning methods: probabilistic and sequential ones. The performance is measured in function of the time needed to access a given position. This position is generated by the uniform random source. After 500 trials the mean time needed to access a random position by the first approach of the probabilistic scan was of 20.4 seconds. For the second approach of the probabilistic scan the mean time needed was of 16.8 and for the sequential scan was of 19.8 seconds. The three results are in the same order but the probabilistic second approach of the scan mode requires less time. Consider now only the right side of the workspace, which is, according to Fig. 3, the most accessed side. The mean time of access for all points belonging to the workspace right side is of 8.4 seconds under the first approach of the probabilistic scan instead of 11.3 seconds corresponding to the second approach of the probabilistic scan mode. Under sequential scan, the mean time is of 14.8 seconds. The probabilistic scan mode first approach is 43% faster than the sequential scan for cells over the right side of the workspace while the second approach is 23.7% faster.

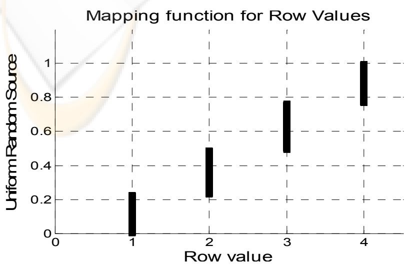

Figure 4.a: Mapping function for the four values of rows.

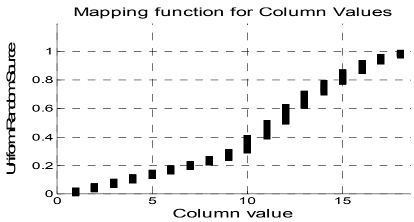

Figure 4.b: Mapping function for the 18 values of columns.

Figure 5 shows how a low probability valued cell in the probability scan first approach evolves after successive callings. The cell passes through the different zones of cells according to its actual probability value. After 240 iterations -or callings-, the cell has passed through three zones and its performance has also been improved as long as its weight. In Fig. 5, one can see that at the beginning, 32 seconds were needed to access that cell.After 240 iterations, only 14 seconds were needed. This time is smaller than the one needed on the sequential scan mode which is of 18 seconds. Fig. 5 also shows when the cell changes zones. Thus, if its probability increases, the cell passes from, for example, *primary zone 2* to *primary zone 1*. Though a cell could be the first in being scanned in the *primary zone 2*, if it increases its value and passes to *primary zone 1*, it could be the last scanned element in this zone. That is the reason of the two time increments in Fig. 5. A cell under the second approach of the probabilistic scan shows similar behavior to the one showed in Fig. 5.

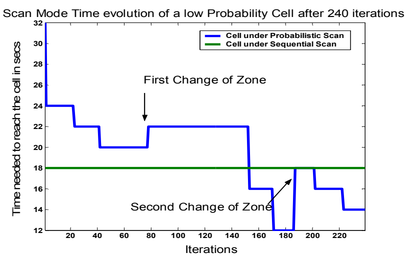

Figure 5: Evolution of a cell access time.

Figure 6 shows the workspace state after 500 iterations generated by the Montecarlo experiment using the first approach of the probabilistic scan. Fig. 6.a shows the probability state of each cell at the workspace while Fig. 6.b shows the new three zones of the scan mode algorithm. One can see that the non-connectivity tends to disappear.

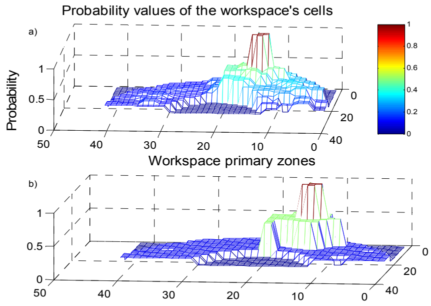

Figure 6: Workspace state after 500 iterations.

On the other hand, Fig. 7 shows the workspace state after the same iterations of Fig. 6 under the second approach of the probabilistic scan, though this scan do not imply a dynamic behavior of the number of cells of the different zones.

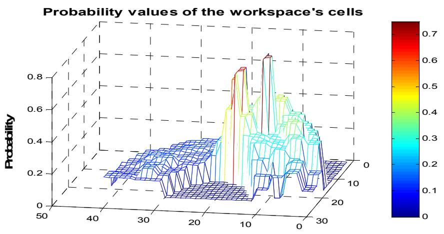

Figure 7: Workspace state after 500 iterations under the second approach of the probabilistic scan mode.

As it can be seen from Figs. 6 and 7, probabilistic distribution of the workspace depends on the type of scan mode used. Both probabilistic scan modes presented in this work show a better performance respect to the sequential scan mode.

5 CONCLUSIONS

The work presented here showed the implementation of two probabilistic scan modes, based on a recursive Bayes algorithm, of a robot manipulator's workspace. A comparison between these methods and a sequential scan mode showed that the probabilistic scan improves the access time of the most frequently accessed cells. Although this system could be implemented in several Human-Machine Interfaces, it was primary designed for a Brain-Computer Interface.

Experimental results show that the time needed to access a specific position at the workspace is decreased each time the position is reached. This is so because the recursive Bayes algorithm implemented updates the probability value of that position once it is reached. A decrement of the access time means that the user of the Interface needs less effort to reach the objective.

In this work, a right-handed workspace distribution case was presented. This case showed that all cells to the right of the middle point -half of the main workspace- have the higher probability and the lower time needed to be accessed.

Finally, it is possible to say that the system learns the user's workspace configuration. It pays special attention to those cells with the highest probability minimizing the time needed to access them.

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