An application of virtual reality for training and ranking operators of mobile robot

Barbara Łukawska[*], Paweł Paduch, Krzysztof Sapiecha

Department of Computer Science, Kielce University of Technology,
Al. 1000-lecia Państwa Polskiego, 25-314 Kielce, Poland

Abstract

In the paper it is shown how candidates for mobile robot operators might be trained and ranked with the help of the specific game running on a computer in virtual reality. It is also shown how playing the game improves their skills and discloses their personal features.

1. Introduction

For years guarding and investigating real environment has been a domain of human activity. However, nowadays more and more often mobile robots are used to this aim. In the case of static environment, planning a minimal robot's tour to see all what is needed is well known problem. The art gallery problem and the watchman problem concern this case and they have already found numerical solutions [1,2]. However, if the environment changes rapidly then a mobile robot is, at least partly, driven by an operator. Human factor is then crucial as far as quality of detecting changes is concerned. Therefore, to achieve the highest investigating quality robot operators can offer, they should be appropriately trained and ranked. In this paper we show how playing a specific game running on a computer in virtual reality can help in this case.

At the beginning of our research we were going to check whether an operator equipped with a map was able to plan an acceptable rout for a mobile robot investigating environment or not. The answer was "yes" [3]. We have observed that some people solve this problem better than others and that investigating quality strongly depends on a human being. That is why we tried next to find a set of attributes characteristic of a super-operator of a mobile robot. The question was whether or not there were some attributes of a human being (age, sex, hobbies, etc) that made him a good operator for a mobile robot. The answer was

---

[*]*E-mail addresses*: {b.lukawska; p.paduch; k.sapiecha}@tu.kielce.pl

"no" but the conclusion was drawn that to disclose human abilities for driving a mobile robot a specific *game* running on a computer in virtual reality could be used [4].

In the paper it is shown how candidates for mobile robot operators might be trained and ranked with the help of the specific game running on a computer in virtual reality. It is also shown how playing the game improves their skills and discloses their personal features. In section 2 a motivation for this research is given. The experiment performed is described in section 3. Experimental results are given in section 4. Finally, section 5 concludes the results.

2. Motivation

In rapid changing environment a mobile robot is driven by an operator. The goal of the operator is to plan a minimal robot's tour to detect every change of the environment before a deadline. Because both the robot and the watched property may be expensive, the robot should not be driven by an occasional person. An operator of mobile robot should detect all changes precisely (be perceptive) and quickly (responding fast but without emotions). Moreover, the operator should draw wise conclusions and be a good and stress resistant strategist. His skills should be as high as possible. Therefore, the operator should be methodically trained. Obviously the training should be neither expensive nor boring.

In the previous work we have developed a simulator of mobile robot [3] and then a game based on the simulator, which makes it possible to evaluate skills of operators of the robot [4][1]. Necessity of answering the question:
- would using the game for training the operators be successful (neither expensive nor boring but decisive), and
- could playing the game help select the most promising candidates for training

seems to be obvious.

3. Training experiment

To answer this question a training experiment was performed where all interesting aspects of improving skill of the operators were investigated. The game running on a computer in virtual reality, described in our previous works [3,4] was applied for arrangement of the training experiment.

The game is similar to a flight simulator. Virtual robot tours a designed *scene* driven by *the player* (robot operator). The scene describes an environment where

---

[1]The game may be played via internet. See http://kin.tu.kielce.pl

objects are placed. The player should detect all scene changes as fast and as precise as possible [3,4]. The detecting quality[2] is calculated and rated.

The operator is equipped with a map of initial scene state. All the objects are marked on the map and described. The player does not know how often the changes occur although he knows that the objects may change position or color, appear or disappear. The player knows *punishment function.* It is based on the number of detected changes, the number of mistakes and the number of commands sent to the virtual robot. He knows that his goal is to minimize this function.

A group of people more or less appropriate for being a robot operator was chosen for the training experiment. The training consisted of two parts:

1. Repetition of games played according to the same rules and in the same environment. Each player repeated the same set of scenes three times during one week.
2. Gradual complication of rules of the game then, that consisted of:
   – allowing the player to go off the predefined path, which forced him to work out the best strategy of touring,
   – stressing the player during the game with random changes in the punishment function.

The player did not know what we were going to analyze in the succeeding experiment phases.

After each attempt at training, a candidate was ranked as "poor", "mediocre" or "good" and put into one of the three corresponding operator groups. The ranking was done according to investigating quality *R* (*R* will be described later on) calculated on line for each of the candidates. The training scheme is shown in figure 1.
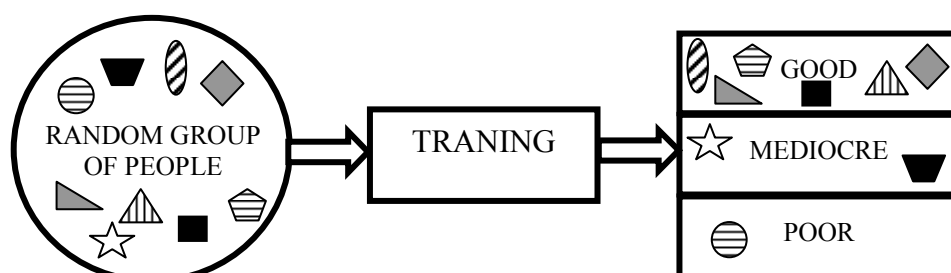

Fig.1. Training scheme

4. Experimental results

The fFirst results, as shown in figure 2, were obtained from an experiment involving a set of inexperienced players (later on we will call them "the

---

[2]The investigating quality is computed from the number of scene changes detected, the number of mistakes made and the number of commands send to the robot.

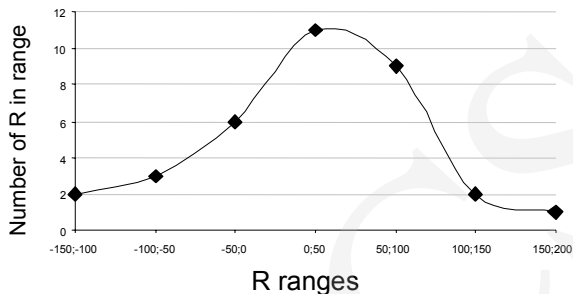beginners"). It was designed to familiarize the beginners with the game and its rules.

Fig. 2. Average number of R in range at the beginning of the training

Investigating quality $R = \mathbf{f}$ (D, D_L, C_w, C_O, C_s, C_p, I, M, P) was calculated for each of the beginners where:

D – % of changes detected;
D_L – % of changes detected too late;
C_W – number of collisions with the walls;
C_O – number of collisions with objects;
C_S – number of times a player went beyond the scene limits;
C_P – number of times a player went off the path;
I – % of incorrectly detected changes;
M – number of moves;
P – number of photos taken.

Next, the beginners repeated three times the same set of scenes chosen in a random order. The average values of R calculated during the consecutive experiment attempts are shown in figure 3.
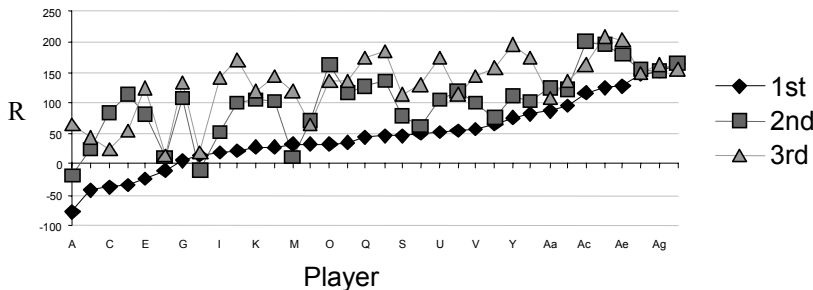

Fig. 3. Average values of R calculated during the training

Finally, the players were put into one of the three following categories:
– "poor" – average value of R < 0;
– "mediocre" – average value of R <0, 100);

– "good" – value of R greater than 100.

More detailed information about player categories is shown in figure 4.
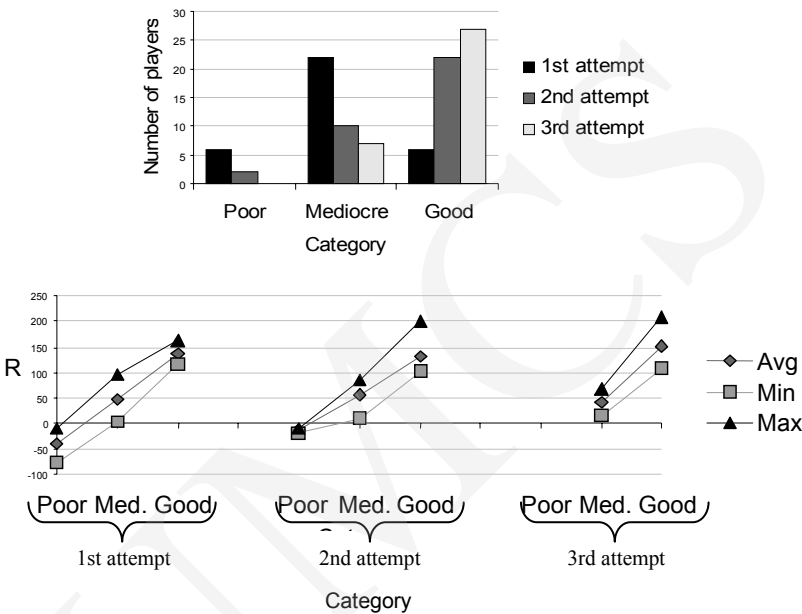

Fig. 4. a) Number of players in each category for every experiment attempt, b) Average, minimal and maximal values of R in each category of the players for consecutive training attempts

In the second part of the experiment the conditions of playing were hardened. Firstly, a player could go off a predefined path, so the player had to invent the best strategy to achieve maximal value of punishment function. Secondly, a player was put under stress conditions being informed randomly that the punishment function had been redefined and then the strategy had to be adopted. In both cases, values of R were calculated and each of the players was put into an appropriate group (Figure 5).
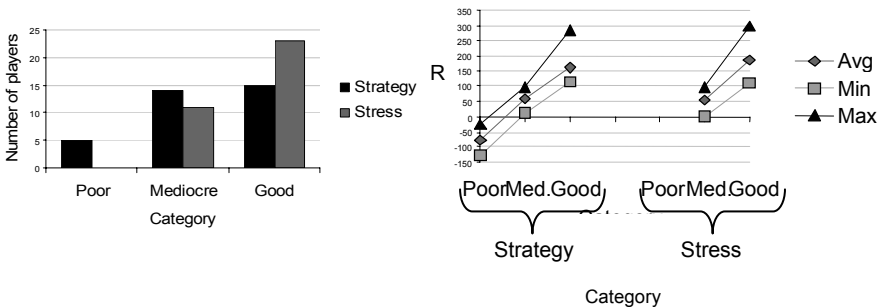

Fig. 5. a) Number of players in each category for bad condition game b) Average, minimal and maximal values of R in each category of the players for hardened conditions

Conclusions

Average values of punishment function for the players at the beginning of the training almost fit normal distribution, which means that candidates for our experiment were chosen properly.

For most of the players the improvement of detecting quality after the training is visible. Anyway, initially very good players have very similar results after the training than before it. So, in their case the training was practically useless, as they have reached their top skills after the first attempt. On the other hand, initially poor players after the training achieved better results than initially good players before it. This means that the training should be tailored individually for each player.

When after each of the attempts each of the players is assigned to one of the three ranking groups: "poor", "mediocre" and "good", then the progress of learning is visible as the passing the players from the lower to the higher ranked groups. "Poor" players become "mediocre", "mediocre" become "good", and the group of "poor" players becomes smaller and smaller. It influences average, minimal and maximal values of punishment function obtained for each of the group in succeeding phases of the training. The global values (average for all the players) increase. However, the same parameters for each of the ranking group do not increase. The parameters may even decrease because many new, initially "poor" players join higher ranked groups.

While the game conditions are getting worse, the players still achieve better and better results in succeeding phases of the training. No matter if there are more or less complicated rules, the training results in better detecting quality. We may suppose that good trained robot operator will do his job well in all conditions.

Finally, the question remains "who is worth the training"? As it was shown, initial player skills, their attitude toward training and abilities for learning were different. Four fundamental categories of individuals can be distinguished as follows: dull and slowly learning (figure 6 sector A), dull and easy learning (figure 6 sector B), clever and resistant to learning (figure 6 sector D), clever and easy learning ones (figure 6 sector E). Obviously, the first group is useless. The last group is the most promising one. Dull and easy learning individuals seem more promising than clever and resistant to learning ones, because they may achieve better results at the end of the training.

Initial skills of the candidates may be evaluated with the help of a single trial (the first phase of the training). Estimation of their learning abilities before the training seems not be possible. The question who wants to be learnt and who actually is learnt remains unanswered.
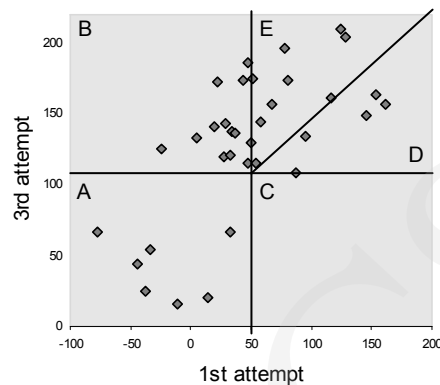
Fig. 6. Types of players

References

[1] Dagnino T., *The Art. Gallery Problem*,
    http://cgm.cs.mcgill.ca/~godfried/teaching/cg-
    projects/97/Thierry/thierry507webprj/artgallery.html
[2] Urrutia J., *Watchman's problem*, http://www.site.uottawa.ca/~jorge/openprob/Watchman/
[3] Sapiecha K., Łukawska B., Paduch P., *Experimental Data Driven Robot for Pattern
    Classification*, Annales Universitatis Mariae Curie-Skłodowska, Informatica, (2005).
[4] Sapieha K., Łukawska B., Paduch P., *System wspomagający profilowanie operatorów
    mobilnego robota*, Zeszyty naukowe Politechniki Świętokrzyskiej, 43 (2005), in Polish.
[5] Fekete S.P., Klein R., Nüchter A., *Online Searching with an Autonomous Robot*,
    http://arxiv.org/PS_cache/cs/pdf/0404/0404036.pdf
[6] Nii Saka Addo, Suor Kim, Eli M Silk, *Navigation Using Behavior-based and Path-planning
    Strategies*,
    http://palantir.swarthmore.edu/maxwell/classes/e28/S00/reports/addo-kim-silk-lab2/
[7] Isler V., *Theoretical Robot Exploration*,
    http://www.cis.upenn.edu/~isleri/research/wpe/wpe.pdf