Realization of the action-oriented education approach by programming a microcontroller steered mobile robot

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Abstract — Focus of this paper is on the development of the action-oriented education approach. Results from secondary data analysis and different empirical studies indicate that for the different levels of education (for example, tertiary practical education as well as operational professional training), enterprises and educational experts expect more competence extension in the future. The concept of action-oriented education which includes informing-process, planning, decision-making, evaluation, examination and achievement should lead the trainee to the development of their own key qualifications, predominantly their own methods and social competence to meet requirements. The concept of action-oriented education is explained by using learning purpose formulation related to the example of the assembly and programming of the microcontroller steered mobile robot. In this context, the role of the trainer is explained, who should be a moderator during his/her instructor's activity in order to increasingly advance the trainees learning and to qualify them in single handed project work and also in groups.

Keywords — component, action-oriented approach, learning styles, learning purpose formulation, expalantion-based learning, mobile robots

I. INTRODUCTION

Even in the case of the same learning conditions, learners achieve different levels of learning success. The reason for it is the fact that, previous knowledge, motivation and basic intellectual abilities of the individual learners are different. Some researchers argue that the reason of the differences in the learning success is that different persons have different skills or preferences with regard to the modeality of the sense, as e.g. eyesight, hearing etc., which is used in learning process. Thus, the different needs and use of the senses as well as the different learning effectiveness are supposed to be a reason for the different learning success levels. Such personality signs and individual preferences are referred to as "learning styles".

II. LEARNING STYLES

Jonassen and Grabowski observe individual differences in the personality with regard to cognitive controls, cognitive styles and learning styles [1]. Cognitive controls are personality signs which influence and control the perception of environmental stimuli. They are narrowly connected to the individual mental skills, and influence more directly than cognitive styles. Besides this, the degree of the influence varies to the extent that the environment influences the perception and understanding of information. According to Paivio's "dual-coding theory," there are two systems independent in their function for the processing of information within the person: the verbal system, which moves information in linguistic form, while the visual system processes information about a mental picture world in the form of spatial images [2]. According to some scientists, the verbal system is connected with the left half of the cerebrum and the visual system with the right half. As stated by Scheu one can also observe a relevant difference among sexes regarding verbal or visual system of stimulation [3]. While girls are much more often acoustically stimulated, boys are stimulated much stronger visually. This takes place in a phase of life where the optical stimulation has a bigger importance than the acoustic ones. It should never be forgotten that learning styles are scientific constructs and the individual use of learning styles changes with the contents, the tasks and institutional circumstances. Also learning styles change by learning and experience. Honey and Mumford see the learning styles as a learning process [4]. They define a four level model, according to which learning takes place in following four phases. First phase is to gain the experience about the subject. It includes the collection of data from investigations and personal experiences. Second phase is called reflection. During reflection one thinks about this gained experience. In this step observation and reflection lead to an analysis of the importance of the data which becomes reviewed and analyzed. Drawing conclusions from the experience is a further step. It means that the abstract formation of concepts generates abstract drafts, models and patterns of thought. The last step is testing of drafts in new situations, explaining new actions,
maximizing the desired effects and examining the model and planning further steps. These four phases then lead again to new experiences, so that this cycle continues on and on. The self-evaluation of one's own learning style does not agree often with the really used learning style if this is determined in observations. Nistor and Schäfer speak even about task-induced learning styles [5]. According to Nistor and Schäfer, solution finding to one favored tasks led to significant learning increase compared with the tasks which unwillingly have to be solved. Thus, learning styles are depending on the nature of the problem and the nature and skills of the individual, and are different as the case arises. But, can still give us helpful tips for the didactics of learning scenarios and learning environment.

III. LEARNING BEHAVIOUR

Learning styles according to Kolb belong to the best-known differentiations of the learning styles [6]. Learning occurs in the aftermath on the basis of experiences and is an ongoing process [7]. Kolb lays great emphasis on the processing character of learning. He distinguishes four learning styles. These are 1) diverging, which includes feeling and watching, 2) assimilating, which includes watching and thinking, 3) converging, which includes doing and thinking and finally 4) accommodating, which includes doing and feeling. Watching and thinking style explain how experiences are collected. Doing and thinking style and doing and feeling style cover how the experiences are processed afterwards [7]. The observation of the original names or descriptions of the learning styles show that Kolb lays great emphasis on the behavior and not on the typology of persons. Kolb analyzes the learning behavior of students, namely the cognitive requirements of particular domains, such as engineering, social sciences and political science. He draws the conclusions about the connection between the learning type and the knowledge domain [7]. While he saw engineers predominantly as a converging type of learners, he found the social scientists and political scientists rather in the divergent domain and the economists in the assimilative area. The diverging type of learners as well as the converging type of learners took part intensely in the on-line learning activities and have been cooperative. The diverging types of learners are also pleased to cooperate, though they commented partially critically on the success of the team. The converging type of learners showed rather a trend towards individual work. The accommodating type of learners accepted highly virtual learning surroundings and took part in on-line tasks. Nevertheless, they used less time and found the available resources and the support by the seminar leader rather insufficient. At the end of the learning process, they estimated their learning success lower than the other learning types. The assimilating type of learners moved in an average area concerning acceptance and learning motivation. They got along well with the tasks and in general with the virtual learning surroundings without major problems. Learners, in general, tend to minimize their learning effort. Nistor and Schäfer [5] formulated the hypothesis of learning style. They defined so called oriented learning effort minimization at the University of Munich, with the help of two virtual seminars oriented to the problem. According to their hypothesis, the learners will organize their own learning process in virtual surroundings so that they can increasingly use their preferred learning style. The researchers find out that the hypothesis is confirmed if the condition is fulfilled that the learning surroundings offer enough degrees of freedom for the purposes of self controlled learning. For this reason, the form and the kind of the learning of the students is an essential social and common aspect, but also the transmission direction of the form of learning on the robot, in order to enable him with possibility to solve own tasks with more autonomy. Today's robots are programmed not only for certain tasks. These should be enabled rather to solve own assignments by independent learning through the integration of the artificial intelligence.

IV. ROBOT LEARNING BEHAVIOUR

Mobile robots are ideal tools to investigate “intelligent behavior”. When we want to define robot’s behavior, it’s necessary to speak of the robot’s environment interactions and the resulting behavior [8]. The behavior of a mobile robot (i.e., what is observed when the robot interacts with its environment) is the result of the robot’s programming alone, but the result of the synergy of three fundamental components (Fig.1.):

1. The program running on the robot (the “task”)
2. The physical platform of the robot (the way its sensors and motors work)
3. The environment itself (how visible objects are to the robot’s sensors etc.)

One phenomenon that is frequently observed in nature and increasingly modeled using mobile robots is that of learning, i.e., adaption of behavior for responding to environmental changes in real time. Typical “things” that are learned by robots are “how” to perform various behaviors: obstacle avoidance, navigation problems, planning robot control etc. It
is important to the choice of the robot’s task. This is inextricably linked to the robot type and to the available sensors and actuators. It is difficult to define a coherent experimental method for robot learning [9]. There is no canonical set of robot learning benchmark tasks. That is partly because the robot’s behavior may be the product of the robot’s learning algorithm, its initial knowledge, some property of its sensors, limited training time, stochastic actions, real-time responses, online learning, the environment or of an interaction between some subset of these. All of these make it very difficult to interpret the results. The robot learning experiments must be designed so as to generate meaningful results in the face of such complexity. In robotic learning, we can distinguish two supervised paradigms; inductive concept learning and explanation-based learning, and two unsupervised paradigms; reinforcement learning and evolutionary learning [10]. Inductive concept learning, assumes that a teacher presents examples of the target function for the robot. In this paradigm, the temporal credit assignment problem is non-existent, since the teacher is essentially telling the robot what action to perform, in some situation. In explanation-based learning, the teacher not only supplies the robot with example of the target function, but also provides a domain theory for determining the range of useful sensory situations. It can be a logical function or a neural network, or even an approximate qualitative physics-based theory. In reinforcement learning, the learner does not explicitly know the input-output instances, but it receives some form of feedback from its environment. The feedback signals help the learner to decide whether its action on the environment is rewarding or punishable. The learner thus adapts its parameters based on the states (rewarding/punishable) of its actions. Evolutionary learning is very similar to reinforcement learning in that the robot is only provided with a scalar feedback signal, but the difference is in term “learning” (online vs. offline learning). The robot system is highly state-dependent, which is typical for real-time embedded systems. Each state and transition of the robot state machine must be associated with the corresponding activity that describes the algorithm that is implemented whenever the component is in that state or triggers that transition [11]. Essentially, we can define the robot learning as one of learning a policy function P from some set of sensory states S to some set of actions A. Examples of policy functions include control behaviors for mobile robots such as avoiding obstacles, following walls or moving a robot arm to pick up some object.

V. ACTION ORIENTED LEARNING APPROACH IN MOBILE ROBOT REASONING SYSTEM

The concept of the so called “comprehensive learning” does not distinguish between the bare condition of the learning (perception by the senses) on the one hand and the cognitive process necessary for the understanding on the other hand. Instead, a so called “action orientation” is considered as an alternative to cognitive dominated learning form. Often in literature action orientation is wrongly minimized to the practical activity; to pure actionism. However, the action-oriented learning refers to the importance of own activity and own control system in the learning process. In action research, the research process is seen as a spiral activity going through repeated cycles and changing each time [12]. The primary strength of an action-oriented or participatory approach to research is therefore not about description but about trying things out. It is a research approach that sees its function as one of giving us different ways of relating to environments [13]. The model of the “entire action” exists of three parts: planning, execution and control. These three areas were further divided in area of action-oriented learning approach in:

<table>
<thead>
<tr>
<th>(1) Data acquisition/ Informing process</th>
<th>(2) Planning</th>
<th>(3) Decision making</th>
</tr>
</thead>
<tbody>
<tr>
<td>(4) Realization/ Completion</td>
<td>(5) Examination/ Checkup</td>
<td>(6) Appraisal</td>
</tr>
</tbody>
</table>

(1) Data acquisition – perception, conceptualization, recognition

(2) Planning – task planning in scope of intervention-goal establishment

(3) Decision making – decision maker knowledge on basis of set of alternatives and the choice of appropriate option according to the established criteria

(4) Realization/Completion – includes the criteria for the evaluation of the utility of the alternatives, for achieving the intervention-goal

(5) Examination /Checkup - nominal/actual value comparison referring to task

(6) Appraisal – mobile robot evaluates its general realization of the task and ascertains if the task is realized according to defined criteria. Another neural network which was already coached and which takes over the task of the instructor or trainer compares the results of the appraisal and examination of the mobile robot and defines possible divergences. Divergences are used for the improvement of the task.

Action-oriented approach in this research is implemented in explanation-based learning form of mobile robot. Humans appear to be capable of making generalizations from a few examples i.e., humans bring considerable amount of background information to the learning task [9]. The explanation-based learning paradigm in our research is based on an approximate qualitative physics-based theory and a lot of sensory information from CMUcam vision system. The domain knowledge is a model of each action, gathered during a previous color-tracking task. This color-tracking task uses a set of camera’s parameters in order to find a colored object and to move towards it. The domain model defines sequences of actions, which defines robot behavior during the robot’s movement to the colored ball. The action model nets can be used to analyze sample state trajectories where the robot arrives. The difference between the calculated and measured robot distance in front of the object provide possibility of
learning the relationship between a given input action pattern and the desired output pattern (object position), so that adaptive data processing can be achieved.

VI. EXAMPLE OF ACTION-ORIENTED APPROACH IN MOBILE ROBOT SYSTEM

According to the areas of the action-oriented approach, we define following stages of the experiment realized with the mobile robot.

A. Data acquisition – perception, conceptualization, recognition

A microcontroller steered mobile robot used for this experiment is Boe-Bot by Parallax, presented in Fig. 2. This robot has two wheels, two motors and a CMUcam1 AppMod vision system for tracking color task. This camera can detect stationary and moving objects. CMUcam1 is an SX28 microcontroller interfaced with a OV6620 Omnivision CMOS camera on a chip that allows simple high level data to be extracted from the camera's streaming video. Only the corresponding array of feature's data is used for Tracking Color Task. From M type packet for our experiment, we used only some dates: Mx - the middle of mass x value, y2 – the right most corner's y value and confidence (pixely/area)*256 of bounded rectangle.

The robot behavior is based on tracking color of a red ball. The ball has been placed at distances D from 15cm to 75cm from robot origin at 10cm intervals and repeated along 17 lines which connect robot origin and ball by 10° angles from 0° to 180°.

For proposed set of ball positions \((\theta, D)\), we gathered 119 experimenter’s patterns (17 different angles and 7 different distances):

<table>
<thead>
<tr>
<th>Ball position ((\theta, D))</th>
<th>Mx</th>
<th>Y2</th>
<th>Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>(170,10)</td>
<td>80</td>
<td>143</td>
<td>114</td>
</tr>
<tr>
<td>(150,50)</td>
<td>80</td>
<td>30</td>
<td>102</td>
</tr>
<tr>
<td>(90,70)</td>
<td>45</td>
<td>4</td>
<td>254</td>
</tr>
<tr>
<td>(60,20)</td>
<td>5</td>
<td>131</td>
<td>128</td>
</tr>
<tr>
<td>(20,60)</td>
<td>5</td>
<td>127</td>
<td>32</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

B. Planning – task planning in scope of intervention-goal establishment

“Tracking of ball color” can be divided into two tasks: finding the red colored ball and moving to the ball through set of actions (A1 – Turn left for 10°, A2 - Turn right for 10° and A3 - Forward). Each robot movement starts with A0 value - it is the number of turns, before the robot can “see” the red ball and it can be 0 too. After that, the robot starts moving towards a ball in action’s sequence. For proposed set of ball positions \((\theta, D)\), we gain the next sequences of robot actions:

<table>
<thead>
<tr>
<th>Position ((\theta, D))</th>
<th>Set of actions (N_{i,j}, i=1..17, j=1..7)</th>
<th>Offset turns A0</th>
</tr>
</thead>
<tbody>
<tr>
<td>(170,10)</td>
<td>A1 A1 A1</td>
<td>5</td>
</tr>
<tr>
<td>(150,50)</td>
<td>A1 A1 A3 A3 A3 A3 A3 A3 A3</td>
<td>4</td>
</tr>
<tr>
<td>(90,70)</td>
<td>A3 A3 A3 A3 A3 A3 A3 A3 A3</td>
<td>0</td>
</tr>
<tr>
<td>(60,20)</td>
<td>A2 A2 A2 A2</td>
<td>0</td>
</tr>
<tr>
<td>(20,60)</td>
<td>A2 A2 A3 A3 A3 A3 A3 A3 A2</td>
<td>5</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

If the angle between the line which connect robot origin and ball and x-axis of robot body in \((0°, 90°)\) domain, then we...
have all A2 actions. If this angle in (90°, 180°) domain, we have all A1 actions. Robot halts at few centimeters in front of the ball.

C. Decision making

Visual recognition and manipulation of the objects occur through the usage of the command Track Color SEROUT 7, 84, [" TC 30 240 16 30 16 30 ", CR]. This command represents min and max data of the RGB color spectrum (red green blue). The camera sends data back by means of the command SERIN 9, 84, [STR RcvData\10]. These data contain the following bytes:

- 0 Byte always 255
- 1 Byte has always character M
- 2 Byte is centre of the mass with coordinates X
- 3 Byte is centre of the mass with coordinates Y
- 4 Byte – left corner of the coordinate X
- 5 Byte – left corner of the coordinate Y
- 6 Byte – right corner of the coordinate X
- 7 Byte – right corner of the coordinate Y
- 8 Byte – number of pixels
- 9 Byte – data reliability /confidence

If no object is detected all the data above are 0. For the purposes of the program following data has been used:

- RCVData(2)- centre of the mass with coordinates X
- RCVData(8)- number of pixels within the window
- RCVData(9)- data reliability regarding the color

For instance, centre of the mass with coordinates X which is in the middle of the window is 45. Widow of the camera is inverted, which means that, if we get the data greater than 45, the object is left behind the centre. In that case, the robot needs to turn to the left.

Possible states are represented in following pseudo-cod:

Step 1: Start, Move = 0
Step 2: Send command “Track Color” in order to get back the array of the data
If RCVData(2)>65 &RCVData(9)>25 then Move = 1; A1 action (move of the robot to the left) else
If RCVData(2)<25 &RCVData(9)>25 then Move = 1; A2 action (move of the robot to the right) else
if RCVData(8)<140&RCVData(9)>25 then Move = 1; A3 action (move of the robot straight ahead) else
If RCVData(8)>140 then Move = 1, A4 action (stop the move) else
If Move = 0 then A1 action (move of the robot to the left) else
Send command “Track Color” in order to get back the array of the data and go to Step 2.

D. Realization/Completion

In this part of action-oriented approach, we make knowledge on the basis of a set of alternatives and the choice according to the established criterion. After analysis of the experimenter’s pattern, we introduce the 5 coefficients, which describe the robot behavior as actions sequence:

- K1 – number of turn before robot “see” the ball (=A0)
- K2 - number of repeated actions A1/A2
- K3 – number of repeated actions A3
- K4 – number of repeated actions A1/A2
- K5 – number of repeated actions A3

We introduce here the term of “Finite State Acceptor” (FSA) [14], which describes aggregations and sequences of behaviors. They make explicit the behaviors active at any given time and the transitions between them. FSA are best used to specify complex behavioral control systems where entire sets of primitive behaviors are swapped in and out of execution during the accomplishment of some high-level goal.

FSA of robot behavior in our experimental research (presented on Figure 4.) can be written in the following form:

\[
M = \{S, \{A0, K1\}, \{A1, K2\}, \{A3, K3\}, \{A4, K4\}, \{A4, K5\}, \{A4\} \}
\]

\[
0^\circ < th < 90^\circ \quad M = \{S, \{A0, K1\}, \{A2, K2\}, \{A3, K3\}, \{A2, K4\}, \{A3, K3\}, \{A3, K5\}, \{A4\} \}
\]

\[
90^\circ < th < 180^\circ 
\]

Figure 4. presents action model of robot behavior. The domain variables represented as nodes are actions. The arcs in figure reflect the different influences between the domain variables. For example, actions A1 can be repeated K1 or K4 times, depending of position in sequences of actions. A0 has arcs to A1 and A2 actions, which depends on the robot moving to the left or right side.

![Figure 4. Action model.](image-url)
For above examples in Table III, we propose the next array’s interpretation of this robot behavior in Table IV:

<table>
<thead>
<tr>
<th>K1</th>
<th>K2</th>
<th>K3</th>
<th>K4</th>
<th>K5</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>7</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>8</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

It is interesting for us, what this array presentation denotes. Namely, the robot goes towards the ball with a displacement 6*K3 at an angle (90°-10°*(K1+K2)). It is the vector $\vec{R}_1$.

Further movement is presented with vector $\vec{R}_2$ with a displacement 6*K5 at an angle 90°-10°*(K1+K2+K4)) in case 0° < $\theta$ < 90°. Number 6 presents distance step (in cm) during moving.

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Resulting vector $\vec{R}$ is result of robot moving towards a ball:

$$\vec{R} = \vec{R}_1 + \vec{R}_2$$

$$R = \sqrt{x_R^2 + y_R^2}$$

where

$$x_R = 6 \times K_3 \cos(\theta_1) + 6 \times K_4 \cos(\theta_2)$$

$$y_R = 6 \times K_3 \sin(\theta_1) + 6 \times K_4 \sin(\theta_2)$$

$$\theta_1 = 90° - 10° \times (K_1 + K_2),$$

$$\theta_2 = 90° - 10° \times (K_1 + K_2 + K_4),$$

$$0° < \theta < 90°$$

$$\theta_2 = 90° + 10° \times (K_1 + K_2),$$

$$\theta_3 = 90° + 10° \times (K_1 + K_2 + K_4),$$

$$90° < \theta \leq 180°$$

E. Examination/Checkup

This step contains comparison of the data resulting from calculations from explanation-based learning robot behavior’s actions with the measured results. This step contains the settlement of the final conditions if the right corner of the coordinate Y of object is greater than 140. On account of the data made available to the robot and the comparison of nominal / actual value, it decides if the condition is fulfilled. In the case that there is enough of red color under the robot so that condition RCVData(8) >140 is fulfilled, robot stops its moving.

F. Appraisal

This step contains comparison of the expected data measured by the person/trainer with the examination done by the robot in step 5. It means that fully optimization of the robot motion requires additional appraisal of the results by the expert. In our case the expert is still the trainer (human being). In further developments also this step should be undertaken by the robot.

Divergences to the calculated value are depending on the corners and are taken into consideration in the calculation of the action. Therefore slight divergences can occur concerning the corner movements. The movement of the robot concerning the covered distance is similar. It means that this distance is not always constant. Concerning the measured values, divergences appear, because of the impact of the camera qualities as well as the impact of the level of the color recognition. The comparison of the values is important in order to ascertain which movement of the robot is still necessary, so that this takes the ball optimally and brings back on the starting point.

VII. CONCLUSION

In this paper we have introduced the application of the action-oriented learning approach by using a mobile robot as the learning object. We have translated the suggested concept of the action-oriented learning approach, from the domain, human-social relations into the domain, trainer (person)-robot. Because the main learning increase by human beings is during visual learning, we have adequately used experiment where we worked with data acquired by a visual sensor (camera). We have realized explanation based concept and formed the artificial knowledge by programming the mobile robot. With it, further step of introducing of the neuronal network is made; so that in the next application, neuronal network can act as the robot trainer instead of the human trainer and can independent...
undertake the appraisal task (step 6) of the action oriented approach.

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