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A Real-World Experiments Setup for Investigations of the Problem of Visual Landmarks Selection for Mobile Robots

Anna Gorbenko

Department of Intelligent Systems and Robotics
Ural Federal University, 620083 Ekaterinburg, Russia
gorbenko.ann@gmail.com

Vladimir Popov

Department of Intelligent Systems and Robotics
Ural Federal University, 620083 Ekaterinburg, Russia
Vladimir.Popov@usu.ru

Abstract

We consider a real-world experiments setup for investigations of the problem of visual landmarks selection for wheeled and tracked robots navigation. In particular, we consider visual landmarks selection in case of one-dimensional panorama.

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The representation of knowledge of the surrounding world plays an important role in mobile robot navigation tasks (see e.g. [1, 2, 3]). Quality of visual navigation methods which use landmarks depends critically on the method of selection of landmarks. In [4], the authors have considered an approach utilizing reinforcement learning to learn a strategy that allows a robot to succeed in a goal-directed navigation task. In particular, the robot is asked to drive to certain location from any position within the environment. The robot learns to select an action for every given observation of the world. In [4], the authors have considered a world with different distributions of landmarks, ranging from a small to a very high number of landmarks, and also one world with landmarks only at intersection points (see Figure 3 in [4]). In [4], it is shown experimentally that learning success critically depends on the number of landmarksthe more there are, the longer learning times are observed. In

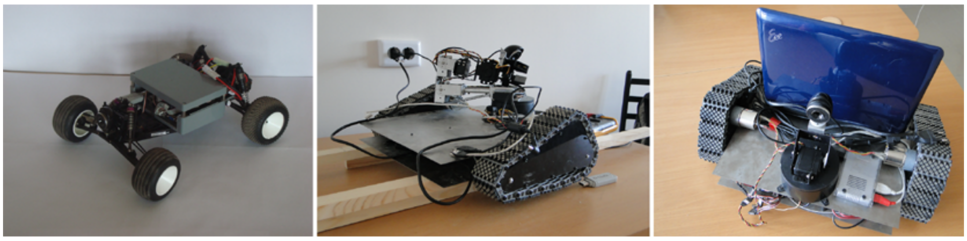

Figure 1: Kuzma-I.3 (left), Kuzma-II.2, Kuzma-II.3 (right).

particular, with few landmarks the learning performance is extremely good. It gets obvious that landmarks only at intersections are sufficient to succeed in the task. On the other hand, for the huge number of landmarks in the fourth world, a stable success rate of 100% has not been reached yet even after 50,000 learning episodes. In [5], the authors have noted that due to performance limitations, many real-time navigation systems are restricted to the use of only a very small number (usually 4-10) of landmarks. Such limitation arises from the large overhead of detecting and tracking these landmarks along the image sequence. In particular, in [6], for example, the authors have presented a navigation system where only four landmarks are simultaneously tracked. In this paper we consider a real-world experiments setup for investigations of the problem of visual landmarks selection for wheeled and tracked robots navigation.

We use different modifications of wheeled and tracked robots (see Figure 1). Design of Kuzma-I.3 based on the well-known RC cars. From RC-CAR AT-10ES Thunder Tiger we use only the four wheel chassis, the high torque DC-MOTOR and a steering servo. The robot is equipped with one rigidly fixed USB web camera. Design of Kuzma-II.2 based on the well-known Johnny 5 Robot. The robot is equipped with Lynxmotion robotic arm with wrist rotate. One USB web camera rigidly fixed on robotic arm. Also, the robot uses a camera of onboard laptop. Kuzma-II.3 is equipped with a 2 DOF robotic camera. Also, the robot uses a camera of onboard laptop.

We consider different types of systems of landmarks. In particular, following [7] (see also [8, 9, 10]), the location signature was made up of zone of monotonically increasing or decreasing intensity in a grey-levelled one-dimensional 360° panorama. In contrast to [7, 9], where used a camera pointing up at the bottom of spherical [7] or conical [9] mirror, to obtain a 360° panorama, we use robotic camera of Kuzma-II.3. A 360° panorama constructed from three 180° panoramas. We consider any point of color change in a grey-levelled one-dimensional 360° panorama as landmark. Respectively, we suppose that $F_1, F_2, \ldots, F_n$ is set of features where $n = 480$, $\mathcal{F}_i = \{0, 1, \ldots, 255\}$. In this case we have a set of landmarks $\mathcal{L} = \{L_1, L_2, \ldots, L_k\}$ where $k \leq 7680$.

Following [11], we consider a one-dimensional array of RGB (red, green,

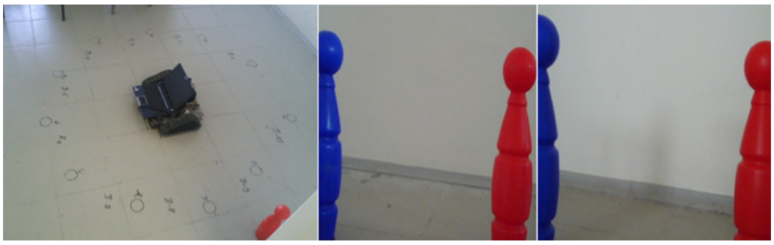

Figure 2: In view of errors of the robot motion, different snapshots represent different sectors of the circular diagram. To demonstrate the accuracy of the robot motion, colored skittles are placed in the vertices of a regular hendecagon.

blue) values extracted along a circle in the two-dimensional colour image as the location signature. Also we consider a one-dimensional array of HSL (hue, saturation, luminance) values (see e.g. [12]). Besides, we consider intensity, color, and orientation as visual cues. In particular, we use two opponent colors red/green and blue/yellow [13] (see also [14, 15, 16]).

In addition, instead of using a 360° unidimensional vision field, we use a sequence of eleven snapshots. In view of errors of the robot motion, different snapshots represent different sectors of the circular diagram (see e.g. Figure 2).

Also, we use colored skittles in different indoor environments as a system of artificial landmarks (see e.g. Figure 3). For recognition of colored skittles, we use sequential processing by neural network (left images) and then threshold transformation (right images) to detect colored regions.

Each colored region we can consider as a sequence of vertical segments with coordinates $(y[1,1], y[1,2]), (y[2,1], y[2,2]), \dots, (y[m,1], y[m,2])$. Also each colored region we can consider as a sequence of horizontal segments with coordinates $(x[1,1], x[1,2]), (x[2,1], x[2,2]), \dots, (x[n,1], x[n,2])$. Each colored region is characterized by vector

$$w[1], \dots, w[80], h[1], \dots, h[40], \delta l[1], \dots, \delta l[10], \delta r[1], \dots, \delta r[10]$$

where

$$w[i] = \frac{\sum_{j=1+(i-1)\lceil \frac{n}{80} \rceil}^{i\lceil \frac{n}{80} \rceil} (x[j,2] - x[j,1])}{\lceil \frac{n}{80} \rceil},$$

$$1 \le i \le r, r = n - 80\lfloor \frac{n}{80} \rfloor,$$

$$w[i+r] = \frac{\sum_{j=1+(i-1)\lfloor \frac{n}{80} \rfloor + r\lceil \frac{n}{80} \rceil}^{i\lfloor \frac{n}{80} \rfloor + r\lceil \frac{n}{80} \rceil} (x[j,2] - x[j,1])}{\lfloor \frac{n}{80} \rfloor}, 1 \le i \le n - r,$$

$$h[i] = \frac{\sum_{j=1+(i-1)\lceil \frac{m}{40} \rceil}^{i\lceil \frac{m}{40} \rceil} (y[j,2] - y[j,1])}{\lceil \frac{m}{40} \rceil},$$

Figure 3: Colored skittles in different indoor environments used as a system of artificial landmarks.

$$1 \leq i \leq l, l = m - 40\lfloor \frac{m}{40} \rfloor,$$

$$h[i+l] = \frac{\sum_{j=1+(i-1)\lfloor \frac{m}{40} \rfloor + l\lceil \frac{m}{40} \rceil}^{i\lfloor \frac{m}{40} \rfloor + l\lceil \frac{m}{40} \rceil}(y[j,2] - y[j,1])}{\lfloor \frac{m}{40} \rfloor}, 1 \leq i \leq m-l,$$

$$\delta l[k] \in \{|x[i,1] - x[j,1]| : 1 \leq i < j \leq n\}, 1 \leq k \leq 10,$$

$$|\delta l[1]| > |\delta l[2]| > \ldots > |\delta l[10]|,$$

$$x \in \{|x[i,1] - x[j,1]| : 1 \leq i < j \leq n\} \setminus \{\delta l[1], \delta l[2], \ldots, \delta l[10]\} \Rightarrow$$

$$x < |\delta l[10]|, \delta r[k] \in \{|x[i,2] - x[j,2]| : 1 \leq i < j \leq n\},$$

$$|\delta r[1]| > |\delta r[2]| > \ldots > |\delta r[10]|,$$

$$x \in \{|x[i,2] - x[j,2]| : 1 \leq i < j \leq n\} \setminus \{\delta r[1], \delta r[2], \ldots, \delta r[10]\} \Rightarrow x < |\delta r[10]|.$$

Such vectors are used as landmarks. They are also used to compare detected regions and landmarks.

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