The autonomous social robot control based on the situation analysis

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Abstract. The problem of the autonomous task solution by the robotic system is considered in this paper. An approach based on the situational assessment and analysis is proposed for this. This approach makes it possible to plan the robot actions from the point of minimizing the situations informational uncertainty. The hierarchical semantic descriptions of the target task, environment and the robot’s state were proposed. Within this approach the situational uncertainty in terms of informational entropy estimates. Each action, including planning, should be aimed to reduce entropy. An example of the proposed approach implementation for the object delivery task was demonstrated. The efficiency of the approach was shown.

1. Introduction
Today robotics is one of the most relevant and promising areas. Almost all modern industry is built on robots. And soon we will not be able to imagine our daily life without robots. Currently, medical robotics and assistant robots [1–3] are developing rapidly, and social robotics has also been actively developing in recent years. Social robot—a such type of robot that can interact and communicate with people in public places in an Autonomous or semi-autonomous mode [4, 5].

An expansion and complexity of the tasks solved by social Autonomous robotic systems (ARS) requires the development of new technologies of the current and predicted situations analysis and understanding.

Based on the situation assessment, the reasonable decisions about the strategy about specified target tasks could be made by the ARS. Due to the variety and complexity of the appeared situations, the situation analysis technologies have an heuristic nature in most cases.

The aim of this work is formation of such informational models of situations and goals that allow planning and solving a wide range of tasks autonomously and in a reasonable manner.

An approach based on the use of informational theory methods for constructing situational models and assessing their complexity the article is considered [6, 7]. Information parameters for evaluating the implemented processes are used: initial, current and final informational entropy, the amount of useful information, the required entropy of successful completion of the target task, and the information performance criterion. These parameters are a universal and could be adapted to describe different situations and states of the robot. The subjectivity in evaluating actions of the ARS could be significantly reduced using of quantitative information assessments of situations and processes.
2. Problem statement

Most modern robotic systems are built according to a modular hierarchical architecture. One or more functional blocks that are responsible for performing the main target task could be commonly defined. These blocks plan the task solution and send commands to other auxiliary blocks. For example, the targeting unit calculates the coordinates of the desired robot position and sends them to the route planning unit. The route planning unit forms the desired trajectory and transmits it to the mobile platform, that performs it.

In addition to the main task, a number of restrictions are usually laid down in the task statement, for example, in terms of operating time, performance, or reliability. Thus, while planning the task solution, it is also necessary to take into account and continuously evaluate these factors. In real conditions, could appear a situation when there is no solution.

For an autonomous planning of the robot actions, the hierarchical semantic descriptions of the target task, the robot’s and the situation state are proposed. Semantic descriptions allow you to combine different types of object descriptions, take into account their behavior, use abstractions, and use a priori information about their properties [8–10]. This description can reflect the hierarchical structure of the robot, changes in its properties or the properties of the external environment.

However, formation of such descriptions without a description of the target task, including constraints and criteria does not make sense. Thus, the description of the target task is primary, and the remaining elements should be necessary for planning (or realizing) of its solution.

Within the framework of the proposed approach, the entire process of solving task, each implementation step and performed operations could be described in terms of applied informational theory. The evaluation of the parameters of the implemented processes within current tasks is carried out on the basis of statistical information theory. It allows, in particular, to present the work of the observation and control systems in terms of the choice concept.

In each stage, including formalization of the target task, the uncertainties could appear. In information theory, the uncertainty of the situation (or state of the system) is determined by the information entropy $H$. For processes with a finite number of states, the entropy is

$$H = \sum_{m=1}^{M} P_m \log_2 P_m,$$

where $P_i$—probability of the $m$-th event (or state of the described parameter) from $M$ possible ones. However, constructing semantic models, it is not always possible to use the concept of probability. Therefore, we will replace the probability $P_i$ with a fuzzy notion of the reliability of the corresponding outcome.

Each step during the solution of the target task, including it’s planning, should be aimed to reduce entropy. The successful solution of the target problem will correspond to the minimum entropy. Change of the situation’s entropy could be realized either by obtaining new information (from sensors for example) or by influencing to the situation (performing some actions). For this, the robot should include the appropriate tools: sensors (for example, cameras, microphones or rangefinders) and control units (manipulators or a mobile platform).

Therefore, the initial entropy determines the initial complexity of the problem that should be solved. In other words it evaluates the initial situation. The final entropy allows you to assess the complexity of the task after conducting a situation analysis or some of it’s steps.

If the required value of the final entropy $H_{q_f}(X)$ is given, then the condition (2) determines the successful completion of the task

$$H_{q_f}(X) \leq H_{q_f}(X),$$

(2)
Entropy—the uncertainty of the process (situation) changes when useful information is obtained. For example, when the objects searching task by the attribute \( n \) is performing:

\[
I_n = - \sum_{m=1}^{M} P(m) \log_2 P(m) + \sum_{l=1}^{M} \sum_{m=1}^{M} \sum_{k=1}^{K} P(U_{nk} | l) P(m | U_{nk}) \log_2 P(m | U_{nk}),
\]

where \( P(m), P(l) \)—probabilities of objects \( m, l \) presence; \( P(U_{nk} | l) \)—conditional probability of occurrence of the \( U_{nk} \) attribute in the presence of the \( l \) object.

The amount of useful information—\( I_n \), could not be calculated in advance. This value is determined in the calculation process, as it depends on the values that the measured attribute or features take. This fact is important, being the basis for managing information flows in adaptive algorithms.

As it was already noted, current situation (or rather its description) is a complex hierarchical structure. The entropy of a situation consists of the entropy of individual parameters or elements of this description. Thus, for Autonomous planning and solving the target task, the robot must evaluate the current entropy and choose actions that could reduce it (with maximum information content) and satisfy some limitations at the same time.

3. Method

Let a mobile robot (MR) equipped with a computer vision system (CVS) and a manipulator (M) perform the next tasks:

- take the object \( O_1 \) from the point A, which coordinates may be unknow;
- transfer and install it to the point B.

The shape and overall weight characteristics of \( O_1 \) are known.

In General, this task is a typical one and could be divided into the stages shown in the figure 1.

![Figure 1. Stages of the task.](image)

The entropy changes graph at each stage of the process is shown in figure 2.

![Figure 2. Changes of entropy in different stages of the task.](image)
Before each stage, there is some uncertainty of the situation, which determines by the initial entropy (uncertainty) of this situation.

Thus for the first stage (Search of the object $O_1$), the entropy consists at the object coordinates uncertainty at the search area. If the value of the search area—$V$, and the element of the area—which determines by the discretization step $\Delta V$, then

$$M = \frac{V}{\Delta V}.$$  

For the equiprobable density of the objects position from the formula (1) the initial entropy of the first stage became:

$$H_{1b} = \log_2 M.$$  

The possibility of successful search implementation is determined by the sufficient completeness of the search models, including models of: search area, search object, search tools, search conditions. Thus, the uncertainty of the situation at this stage is related to the entropy of the object’s position, which is determined by the particular entropies of the search task.

At the same time, the entropy reduction at this stage is carried out by known means: the definition of areas of interest, the definition of informative features of the object and the search implementation itself. There could be used different algorithms and approaches [11–13] of computer vision. Their informational models became similar like (3).

The variation of entropy over time of the search process is shown in the graph (figure 2, section 1) as a solid bold line. Options the search processes implementation are shown by dash-dotted lines (figure 2), when the search area may have different dimensions or be searched with different efficiency. If the search results determine the coordinates of the object $O_1$ (with probability 1), then the final entropy became zero:

$$H_{1f}(X) = 0$$

and the search process finishes.

Then goes the second stage (figure 2, s.2)—transition of the mobile robot (MR) to the object’s reachability region. This stage includes procedures for route planning and traffic management of the MR. Models of the MR movement and the surrounding space should be used during the route planning. In particular, a digital map of the room is required for the ground MR. The entropy of the planning process is determined by the uncertainty of the trajectories.

The entropy of the robot’s position, as well as the entropy of the robot’s movement (or successful movement) to a given point is used for moving the mobile platform. The total stage uncertainty (initial entropy) for the selected motion path is calculated based on the possible control options at each control cycle.

Controlling of the mobile platform movement, useful information $I$—is information that reduces the uncertainty of the robot’s position.

For example, at each step of the mobile platform control when it moves along a given trajectory, the robot has the opportunity to choose one of 256 directions of movement (the initial entropy of the process $H_0 = 8$ bits). To select one of the directions and reduce the initial entropy to $H_f(X) = 0$, it is necessary to submit $I = 8$ bits of useful information from the control system.

Let, for example, the robot has 8 equally probable variants of elementary directional controls on each cycle, and the control is performed by the frequency of 0.1 Hz. Then the entropy of the robot’s movement during 1 s is 30 bits. It could be determined the initial entropy of the stage, knowing the speed of movement and the distance of the path.

The probability of success of this task becomes 1, and the posteriori entropy becomes maximum, when the robot has reached the desired position. Also, if for some reason it is impossible to move the robot, the posteriori entropy will also be maximized.
When the robot enters the area of the object \( O_1 \) (point A becomes inside the service area of the robot, in other words in the area of the manipulator), the robot takes the working position (stage 3), moves the manipulator to the point that ensures the reachability of the object by the gripper, and captures the object.

If the position of the object is known and the trajectories of the manipulator and gripper are determined, then the control entropy is calculated by the same way as in step 2 when the MR moves.

Stage 4 is implemented similarly to stage 2 and includes procedures of planning the route to the point B and the robots mobile platform control performance.

Step 5 starts its implementation when the point B becomes inside the robot’s service area. The mobile robot takes a working position, moves the manipulator to the required point in space and installs the object \( O_1 \) in point B.

Figure 3 shows a graph of changes of the total entropy of the target task. The process in which the stages are performed sequentially, i.e. the next stage begins only after the successful completion of the previous stage is considered there. As you can see from the graph, the total task completion time is determined by the efficiency of individual stages.

![Figure 3. The total entropy evaluation of the target task.](image)

During the execution of each stage, the criteria and constraints that were set by the target task or the robot’s features should be continuously calculated. In addition to the fact that each action of the robot changes the informational entropy of the situation, it changes some parameter of the situation, for example, time, battery charge, or other resource. Informational bandwidth could combine the change of this resource and the information content of the corresponding action into a single information description. Information bandwidth denotes the processing rate of information \( I \) over time \( T \)

\[
C = \frac{1}{T} \frac{H(X) - H(X | Y)}{T} \text{ [bit/sec]. (4)}
\]

In this formulation, the bandwidth is understood as the speed of obtaining the useful information. At the same time, the minimization of the execution time of this action could serve as the criterion. If the action changes another parameter, such as the battery charge, you can replace the time parameter in formula (4) to it. As a result, the criterion is to maximize the desired bandwidth, and the limitation is to limit the corresponding parameter. The relationship between actions and the changes of the parameter is laid down inside the situation model and should be recalculated before evaluating each action.

4. Conclusion
The problem of the automatization of the autonomous mobile robotics system target tasks solution is considered in this paper.
An approach based on the construction of a semantic model, of the solving task and the assessment of its uncertainty, based on information entropy is proposed. The solution of the target problem is represented as the choice of the action with the maximum informational bandwidth.

The use of elements of the proposed approach was shown on the example of a typical task of a mobile robot—the transportation of an object. At the same time, it is proposed to combine various criteria and restrictions with the informativeness of the robot’s actions at the expense of a modified information bandwidth.

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