Adv. Studies Theor. Phys., Vol. 6, 2012, no. 25, 1243 - 1246

Robot Self-Awareness: Usage of Co-training for Distance Functions for Sequences of Images

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 use temporal relation based data mining to consider robot self-awareness. We consider the problem of finding regularities among effects of robot's actions and changes of the environment. In particular, we study distance functions for sequences of images.

PACS: 45.40.Ln

Keywords: robot self-awareness, distance function, robot

To use some system of anticipation the robot needs some system of finding regularities (see e.g. [1] – [3]). The representation of knowledge of the surrounding world plays an important role in robot navigation tasks (see e.g. [4] – [6]). Finding optimal solutions for such tasks usually requires to solve some hard problem (see e.g. [7] – [9]). Robot self-awareness and anticipation of some events gives the robot significant additional capabilities to solve such tasks (see e.g. [10] – [15]). In this paper, to find regularities among effects of robot's actions and changes of the environment we consider distance functions for sequences of images. We use mobile robots as main testbed (see e.g. [13]) for our experiments.

Let Σ^* be the set of all words over some fixed alphabet Σ. The length of a word S is the number of letters in it and is denoted as $|S|$. For simplicity, we use $S[i]$ to denote the ith letter in word S. Traditionally the alignment notation has been used to illustrate a comparison between two or more sequences. Given a set of strings $X = \{x_1, x_2, \ldots, x_k\}$ on an alphabet Σ, a multiple alignment of X is a set of strings $A = \{A_1, A_2, \ldots, A_k\}$, $|A_1| = |A_2| = \ldots |A_k| = n$, on augmented alphabet $\Gamma = \Sigma \cup \{\Delta\}$ such that each string A_i is a copy of x_i into which $n - |x_i|$ copies of special symbol Δ have been inserted. Symbol Δ is called an indel and represents the insertion or deletion of a particular symbol in one string relative to another.

A conventional way to measure the approximate similarity between two sequences $a_1 a_2 \ldots a_m$ and $b_1 b_2 \ldots b_n$ is to calculate local transformations or costs of local transformations. Usually the considered local transformations are the following: substitution: $a_i \to b_j$; insertion: $\Delta \to b_j$; deletion: $a_i \to \Delta$.

To define a distance between sequences, one should first fix the set of local transformations and non-negative valued cost function δ that gives for each transformation $a \to b$ a cost $\delta(a, b)$. A penalty matrix specifies the substitution cost for each pair of characters and the insertion/deletion cost for each character. The differences appearing in the considered two sequences can be viewed differently, e.g., one substitution can be viewed as one insertion and one deletion. Therefore, it is natural to observe the minimum number of such differences. The weighted edit distance between x and y is the minimum cost to convert x to y using a penalty matrix.

In some simple cases sufficiently accurate values of the distance function can be calculated relatively easily using genetic algorithms. Accumulation of data on such events can be implemented at testbeds in the automatic mode. Therefore, for such events there is an unlimited amount of data that allow us to train high-quality analyzers. However, anticipation of human actions is of great importance for the robot. In this case, the accumulation of data is much more difficult. These data can not be obtained in the automatic mode. Accordingly, in this case, it is possible to obtain only relatively average-quality analyzers. But even such analyzers for collisions with a human it is very difficult to do. Such collisions can lead to human injury or damage the robot.

The use of both labeled and unlabeled data for practical problems was popularized in [16] in the area of information retrieval. They use Expectation-Maximization to infer the missing labels of the unlabeled data much in the same way that Expectation-Maximization is typically used to infer missing cluster labels. During learning, Expectation-Maximization assigns strong labels to those unlabeled examples which are unambiguous. These new examples sharpen the class density estimates, which then allows for the labeling of additional unlabeled examples. Co-training was proposed in [17] as a method for training a pair of learning algorithms. Co-training based methods for real world problems have been developed and used successfully by several groups.

The basic assumption is that the two learning algorithms use two different views of the data. For example, it is not hard to believe that one can discriminate between apples and bananas using either features of their shape or features of their color. Since the margins assigned by the classifiers are not directly related, there may exist a set of examples with high margin based on shape and small or negative margin based on color. The key property is that some examples which would have been confidently labeled using one classifier would be misclassified by the other classifier. The classifiers can therefore train each other, by providing additional informative labeled examples. Given two views of the data, one might be tempted to avoid training altogether and simply combine the views in order to improve the classification performance. Why then does co-training operate on the views separately, since it reduces classification performance? Co-training is a training process not a classification process. After co-training the final classifiers, which are trained on labeled and unlabeled data, are significantly improved. These improved classifiers are easily combined in order to maximize classification performance. In fact, in [17] proved under a set of formal assumptions, that co-training finds a very accurate rule from a very small quantity of labeled data. This error rate is far smaller than what would be achieved by simply combining the initial classifiers.

For the distance function, there are three following groups of analyzers: high-quality analyzers for environmental effects of actions of the robot and changes of the environment; average-quality analyzers for effects of human actions; low-quality analyzers for human-robot collisions. In our framework co-training used to improve the quality of analyzers for effects of human actions and analyzers for human-robot collisions.

References

[1] A. Gorbenko and V. Popov, On the Problem of Sensor Placement, *Advanced Studies in Theoretical Physics*, 6 (2012), 1117-1120.

[2] A. Gorbenko and V. Popov, The set of parameterized k-covers problem, *Theoretical Computer Science*, 423 (2012), 19-24.

[3] V. Popov, Multiple genome rearrangement by swaps and by element duplications, *Theoretical Computer Science*, 385 (2007), 115-126.

[4] A. Gorbenko and V. Popov, On Face Detection from Compressed Video Streams, *Applied Mathematical Sciences*, 6 (2012), 4763-4766.

[5] A. Gorbenko and V. Popov, Self-Learning Algorithm for Visual Recognition and Object Categorization for Autonomous Mobile Robots, *Lecture Notes in Electrical Engineering*, 107 (2012), 1289-1295.

[6] A. Gorbenko, A. Lutov, M. Mornev, and V. Popov, Algebras of Stepping Motor Programs, *Applied Mathematical Sciences*, 5 (2011), 1679-1692.

[7] A. Gorbenko and V. Popov, Computational Experiments for the Problem of Selection of a Minimal Set of Visual Landmarks, *Applied Mathematical Sciences*, 6 (2012), 5775-5780.

[8] A. Gorbenko and V. Popov, Programming for Modular Reconfigurable Robots, *Programming and Computer Software*, 38 (2012), 13-23.

[9] A. Gorbenko and V. Popov, On the Problem of Placement of Visual Landmarks, *Applied Mathematical Sciences*, 6 (2012), 689-696.

[10] A. Gorbenko and V. Popov, Robot Self-Awareness: Occam's Razor for Fluents, *International Journal of Mathematical Analysis*, 6 (2012), 1453-1455.

[11] A. Gorbenko and V. Popov, The Force Law Design of Artificial Physics Optimization for Robot Anticipation of Motion, *Advanced Studies in Theoretical Physics*, 6 (2012), 625-628.

[12] A. Gorbenko, V. Popov, and A. Sheka, Robot Self-Awareness: Exploration of Internal States, *Applied Mathematical Sciences*, 6 (2012), 675-688.

[13] A. Gorbenko, V. Popov, and A. Sheka, Robot Self-Awareness: Temporal Relation Based Data Mining, *Engineering Letters*, 19 (2011), 169-178.

[14] A. Gorbenko and V. Popov, Anticipation in Simple Robot Navigation and Learning of Effects of Robot's Actions and Changes of the Environment, *International Journal of Mathematical Analysis*, 6 (2012), 2747-2751.

[15] A. Gorbenko and V. Popov, The c-Fragment Longest Arc-Preserving Common Subsequence Problem, *IAENG International Journal of Computer Science*, 39 (2012), 231-238.

[16] K. Nigam, A. K. McCallum, S. Thrun, and T. M. Mitchell, Text classification from labeled and unlabeled documents using EM, *Machine Learning*, 39 (2000), 103-134.

[17] A. Blum and T. Mitchell, Combining labeled and unlabeled data with co-training, *Proceedings of the 11th Annual Conference on Computational Learning Theory*, (1998), 92-100.

Received: September, 2012