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IFAC-PapersOnLine 48-11 (2015) 028–035

Processing and Forecasting the Trajectory of a Thrown Object Measured by the Stereo Vision System

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Abstract: Transportation of small-sized rigid objects in industrial environment may be provided by throwing it from the source point and catching it at the destination point. This approach promises better flexibility than traditional transportation systems based on conveyor belts. Accurate real-time forecasting of the object ballistic trajectory is necessary to provide successful catching of the object by the gripper. The development of a sample-based algorithm for trajectory forecasting is a scope of this paper. The input for the forecast is a reference of object spatial coordinates measured by the stereo vision system. Such measurements allow defining the position of the object in a camera-related coordinate system with millimeter accuracy, however they sometimes include outliers. A reference of coordinate transformations is proposed, which translates object coordinates from the camera related 3D system to a 2D system with relations to gravity and motion direction. Outlier detection is made during these transformations. The forecasting is performed in 2D coordinate system with use of k nearest neighbors approach. Applying the algorithm to the measured trajectories showed that it is able to predict future position of the object with 3 centimeters precision in 92 % of cases.

Keywords: Ballistic motion, Machine learning, Motion estimation, Nearest neighbors, Prediction methods, Robot vision, Target tracking.

1. INTRODUCTION

Transport-by-throwing (TbT) is a novel approach for transportation of small-sized rigid objects, especially in industrial environment (where there is a need to transport a high number of objects between machine tools). It was introduced by Frank et al. (2006). According to this approach the transportation of an object from a source point to a destination point is provided via throwing it at the source point (towards the destination point by the specific throwing device) and catching it at the destination point (by the specific capturing device). Throwing-based transportation systems have potential advantages in comparison with traditional conveyors: better flexibility, higher productivity and lower consumption of energy and resources (Frank et al. (2006)).

While the task of the throwing device is exact - it must throw objects everytime with fixed direction and velocity - the catching challenge is more complicated: the gripper must catch airborne object in a priori unknown interception point at a priori unknown time moment with a priori unknown velocity. The task of catching an airborne object with a robotic manipulator was considered prior to the foundation of TbT as one of common robotic activities. It was introduced by Hove and Slotine (1991). To define catching time, position, and velocity the trajectory of the object is predicted based on the observation of its flight. While most existing approaches on trajectory prediction are based on physical models of the object motion, here we apply a sample-based predictor that does not require exact knowledge about physical parameters of the trajectory. Our predictor uses a modified version of the algorithm proposed by Mironov et al. (2014). The development and validation of the proposed ideas is implemented with tennis ball as a thrown object. The reason is that the tennis balls is a well-known aerodynamic object; there is a number of scientific works exploring the aerodynamic properties of the tennis ball (the review on such exploration is given e.g. by Mehta et al. (2008)). On the other hand most of existing robotic catching applications also deal with small-sized sport balls, e.g. catchers by Hove and Slotine (1991), Frese et al. (2001), Birbach et al. (2011). On the other hand the basic principle of prediction should be independent from the spherical shape of the body and may be extended to the objects of another shapes.

This article is organised in the following way. In the second section quick overview of existing techniques for ballistic trajectory prediction is given. In the third section the collected database of trajectories used for learning and validation is discussed. In the fourth section coordinate transformation reference is discussed. Coordinate transformations are made in order to increase accuracy of prediction, to decrease the complexity of further calculations (e.g. decreasing dimensionality of the data), and to make use of trajectory database more efficient. The last subsection of section 4 is concentrated on prediction

10.1016/j.ifacol.2015.09.155

of object movement in transformed coordinate system. In section 5 evaluation results for the whole algorithm based on the dataset are presented and discussed. In section 6 concluding remarks are given.

2. RELATED WORKS AND CONTRIBUTION

In the first robotic ball catcher developed by Hove and Slotine (1991) parabola fitting was used to estimate and predict the trajectory of the thrown balls. Parabolic motion models were also applied in recent robotic catchers developed by Herrejon et al. (2009) and Batz et al. (2010). In such models gravity is considered as the only significant force, which influence on the flying object, and acceleration of the object is considered as equal to gravity acceleration while the object is airborne:

$$\ddot{X} = \{-g, 0, 0\} \tag{1}$$

where $X = \{x_1, x_2, x_3\}$ is a vector of object coordinates (and axis x_1 is directed upwards), g is gravitational acceleration. The solution of this equation is a well-known formula of motion with constant acceleration:

$$X = X(0) + \dot{X}(0)t + \{-g, 0, 0\}\frac{t^2}{2} \tag{2}$$

where t is time. This model does not consider air drag which may be neglected on short distances and become a significant force on the long term (see, e.g. the simulation of ballistic motion by Tutz (2007)). Further physical models of ball motion, considering gravity and air drag as significant forces were applied e.g. by Frese et al. (2001), Barteit et al. (2008), Birbach et al. (2011). In such models the object coordinates at the certain time moment after the throw may be calculated by solving the following differential equation:

$$\ddot{X} = \{-g, 0, 0\} - k|\dot{X}|\{\dot{x_1}, \dot{x_2}, \dot{x_3}\} \tag{3}$$

where k is a coefficient defining air drag. Unlike (1) this equation has no analytical solution and is usually solved numerically. Such a model is also simplified, however allows achieving 66-80% rate of success in catching (Frese et al. (2001), Birbach et al. (2011)).

Increasing precision of the motion model lead to increasing complexity of calculations and to the need of more complicated experiments in order to define aerodynamic properties of the object. Even for simle-shaped objects like tennis balls complicated experiments in aerodynamic tube are necessary to define drag coefficients (Mehta et al. (2008)). Accurate aerodynamic model of the object is much dependent on its shape. Learning-based methods draw attention as a potential way for trajectory prediction because they do not need exact knowledge about object physical properties to work correct. Kim and Billard (2012) propose the predictor based on process model with parameters obtained by means of machine learning. This approach lies between analytical and learning-based prediction: prediction is performed by integrating tangential and angular acceleration of the object, while these accelerations are estimated based on learning. Later Kim et al. (2014) apply this concept for catching airborne objects with robotic manipulator and achieved 73% success rate. The learning based approaches were introduced by Mironov and Pongratz (2013) - neural network prediction, - and by Mironov et al. (2014) - nearest neighbors.

In this paper we extend and apply the predictor introduced Mironov et al. (2014). Observed trajectory of the object is compared with sample trajectories from the database. The input of the predictor includes the reference measurements of the current trajectory $C(1 : m) = \{X_c(1), X_c(2), ...X_c(m)\}$ where m is a number of frames captured by the observation system till the moment when prediction is made. The database include N trajectories $S_1, S_2, .., S_N$ where each trajectory $S_i(1 : n) = \{X_i(1), X_i(2), ..., X_i(n)\}$ and $n > m$ is overall number of frames. The predictor task is to calculate a forecast of the current trajectory $C(f : n) = \{X_c(f), X_c(f), ...X_c(n)\}$ where $m < f < n$. This task is solved in the following way. Two trajectories $A(1 : n) = \{X_a(1), X_a(2), , ...X_a(n)\}$ and $B(1 : n) = \{X_b(1), X_b(2), ..., X_b(n)\}$ are taken from the database such that measured points of the current trajectory $C(1 : m)$ lie higher than corresponding points of trajectory $B(1 : m)$ and lower than corresponding points of trajectory $A(1 : m)$ and that the distances from trajectories $A(1 : m)$ and $B(1 : m)$ to $C(1 : m)$ are smaller than from any other trajectories from the set. Distance is defined as a mean value of euclidean distances between corresponding points of trajectories:

$$D(A, C) = \frac{1}{m}\sum_{i=1}^{m} |A(i) - C(i)| \tag{4}$$

The forecast $C(f : n)$ is calculated as a weighted mean of $B(f : n)$ and $A(f : n)$:

$$C(f : n) = w_a A(f : n) + w_b B(f : n) \tag{5}$$

Weights w_a and w_b are defined according to the distances from A and B to C. Two extensions of the algorithm were proposed by Mironov et al. (2014). First it was proposed to sort the trajectories in the dataset with respect to launching velocity (or launching angle, or any other parameter characterizing the shape of trajectory) and take in mind only such trajectories from the database that have the same value of thus parameter as C. This allow decreasing the volume of calculations as the current trajectory is compared only with a small subset of the dataset. Secondly, it was proposed to translate the 3D trajectory coordinates into 2D "Plane-of-Flight (PoF)". Goals of this transform are discussed more precisely in subsection 3.2.

Mironov et al. (2014) explored the theoretical usefulness of the kNN approach via the numerical simulation of the object flight. This simulation was including a number of simplifying assumptions. Here we extended the prediction algorithm in order to overcome these assumptions. The main advances in comparison with the work by Mironov et al. (2014) are listed below.

- The model of the object motion based on (3) was used for simulating trajectories. Validation of the algorithm was done based on this simulation. Here we validate our algorithm by forecasting real trajectories of the thrown balls observed by the vision system.
- It was assumed that the center of the coordinate system coincide with the starting point of the object flight and coordinate axis x_1 is directed upwards.