Reactive Collisions Avoidance in Collaborative Robot Environment

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***Abstract*—....**

The implementation is open-source and available at https://github.com/philippluedtke/predictive_collision_avoidance.

***Index Terms*—Collision Avoidance; Human-Robot Collaboration; Real-Time Robot Control; Parameter Optimization**

I. Introduction

A. Relevance in Industry and Academia

Industry 5.0 signifies a pivotal realignment of industrial priorities, emphasising human-centric collaboration, sustainability, and resilience rather than the pursuit of automation for its own value [1]. Building on the digital and cyber-physical foundations of previous industrial advancements, Industry 5.0 utilizes technologies such as the industrial Internet of Things (IoT), artificial intelligence (AI), digital twins, industrial robots and additive manufacturing to facilitate smart factories, while redefining technological progress as a means to empower human workers and reduce environmental impact [2]. The focus of Industry 4.0 was predominantly on efficiency and connectivity, which gave rise to concerns regarding job security, rising unemployment due to automation, and environmental issues such as excessive energy consumption and electronic waste. Industry 5.0 aims to address these social and ecological gaps by augmenting human capabilities through collaborative machine systems, as opposed to replacing them [2].
par Collaborative robots (CoBot) are designed to undertake repetitive or hazardous tasks, thereby allowing human operators to focus on more complex activities such as oversight, problem solving and more value-adding operations [1]. This shift presents a range of practical opportunities, including mass customisation, greater production flexibility, optimised resource use, and the inclusion of disabled people in the workforce. These opportunities can help to meet growing consumer demand for personalised products while lowering material and energy footprints [2].
par Simultaneously, the increased proximity of humans and machines gives rise to new and significant safety challenges. These challenges require robust technical solutions and regulatory guidance to ensure worker protection under all conditions [4]. In practice, common safety systems such as torque sensors provide reliable collision detection and force control. However, they only signal after an impact has occurred. This means that complementary approaches such as proximity sensing offer promising opportunities for achieving anticipatory protection and facilitating smoother and safer human-robot interaction [4]. From an occupational health and safety perspective, human-centred collaboration has been shown to reduce musculoskeletal risk factors, decrease physical effort, improve coordination and efficiency, and lower exposure to hazards. Some experimental studies also report fewer errors per unit of time and maintained trust in cobotic systems, even when total error counts remain similar across conditions [4].
par The societal relevance of human-centred manufacturing is reinforced by legal frameworks such as the § 154 of the German Social Code Book IX that promote inclusion and reasonable accommodations for severely disabled employees. This ensures that industrial practice aligns with broader goals of social participation and equity [5]. ...

B. Hardware

The project uses the following components:

- Microcontroller: Raspberry Pi Pico (RP2040)
- Sensor: VL53L7CX ToF (8x8 grid) (capabale of IR)
- Mounting: One ring made out of six sensors (with dead zones)
- Robotic Arm U10

II. Methodology

A. Tunning Hyper Parameters of DBSCAN

In order to determine the optimal hyperparameters for the DBSCAN algorithm (eps and min samples), we initially employed analytical optimization techniques. The K distance plot is a widely used diagnostic tool for selecting the epsilon parameter for density-based clustering algorithms including DBSCAN. As seen in Figure X and Y, the plot not only conveys a scale for neighborhood density for voxel-based point clouds but also signatures of the underlying grid structure. Mark X of Figure X showcases the elbow point, which is the location of maximal curvature in the K distance curve. In practice, it is the point where the plotted distances change from a relatively flat trend to a markedly increasing slope. Geometrically speaking, this point separates voxels that reside in dense local neighborhoods from points that are isolated or belong to sparse clusters []. Therefore, the vertical coordinate at the elbow is commonly chosen as the epsilon value for DBSCAN []. Points appearing before the elbow have small distance to their k nearest neighbor and therefore belong to

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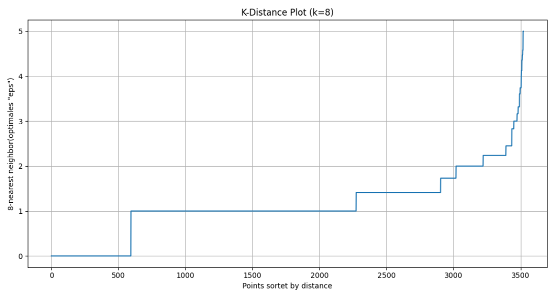
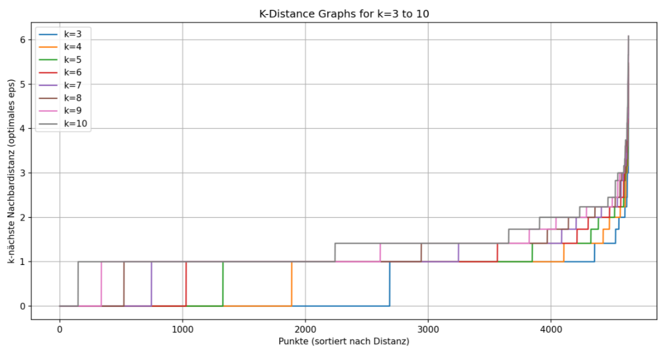


(a) k Distance Plot with single value k = 8



(b) k Distance Plot with multiple values of k

Fig. 1: k Distance Plot from limited random sample

dense cluster interiors. Points that appear after the elbow have substantially larger k distance and are likely to be noise or members of very sparse clusters []. Setting epsilon to the elbow value implements the decision rule: every point whose k distance is smaller than epsilon is considered part of a cluster while points with larger k distance are treated as noise. Points inside clusters tend to have many nearby neighbors so their k distance stays small, and the curve is flat. When the curve reaches the elbow the population of points transitions from cluster interior to boundary or to background. This transition produces the characteristic knee shape that guides epsilon selection. [] Subsequently, the parameter sets that were theoretically derived were validated and fine-tuned empirically using a small representative sample dataset. This process was carried out to ensure the robustness of the application in real environment.

par In this project, voxelized point clouds are defined on a discrete integer grid. Distances between voxel centers are computed with the Euclidean norm

$$d = \sqrt{\Delta x^2 + \Delta y^2 + \Delta z^2} \tag{1}$$

where each delta is an integer difference between voxel coordinates. Because the coordinate differences are integers the set of possible distance values is discrete and limited. When the k distance values for all points are sorted, many points frequently share identical or nearly identical distance values. This results in extended horizontal segments in the sorted curve. Each flat segment corresponds to a bin of identical distance values produced by the grid geometry. When the next larger discrete distance appears, the curve jumps to the next step. The more regular the grid and the coarser the voxel resolution the stronger the staircase effect. The staircase appearance is not a flaw but an artifact of discretization. It implies that small changes to epsilon within a flat segment will not change cluster assignments. Conversely, choosing epsilon values at jump points will change the number of neighbors for many points at once and may cause abrupt changes in the clustering outcome. In practice it is therefore advisable to choose epsilon near the top of a stable flat segment immediately before a jump, or to use algorithms that estimate the elbow by curvature rather than by manual inspection [].

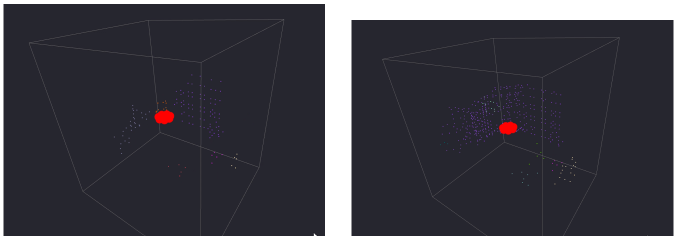
III. Preliminary Results from Testing with Real Sensor Ring Data Input

A. *Preprocessing Static Objects*

Testing with real-time data input led to the identification of various implementation as well as preliminary design flaws in our approach. Despite the program's effective management of the increased data input from six additional sensors, with cycle times ranging from 65 to 75 milliseconds, significant concerns remained. The ability to consistently detect and distinctly differentiate between various objects was found to be inconsistent. A significant cause of these errors was the static surroundings' persistent tendency to group together with nearby moving objects or to merge and subsequently unmerge with other static objects. This behavior led to the distortion of movement and resulting clustering errors as seen in Figure X. However, a substantial adjustment was implemented through the integration of a preprocessing step. Prior to executing the main program, a scan of the environment for static objects is performed. Subsequently, it is assumed that these static voxels do not contain relevant information for object detection. This approach led to a substantial reduction in merging errors as well as noises. However, the method for identifying static objects remains underexplored and requires further development such as a continuous background scan.

B. *Cycle Clock Time*

During the testing phase, it became evident that cycle clock time presented a significant constraint, prompting a comprehensive evaluation of both conventional boolean-based voxels and a continuous time-based approach. Theoretically, the boolean method offers enhanced efficiency by reducing complex floating-point arithmetic to low-latency bitwise operations. However, this computational advantage remains to be empirically validated in our specific test environment. It is essential to note that the boolean approach enables more robust movement reconstruction by treating each time frame as a discrete, independent state. In contrast to time-surface methods, which frequently overwrite historical data with the most recent timestamp, this discrete separation method preserves the complete occupancy history. This capability enables significantly more granular and extended retrospective trajectory analysis. Overall, the advantages of the time-based method



(a) Case 1: Clear differentiation of objects

(b) Case 2: Merging of Object due to closeness

Fig. 2: Merging phenomena of unrelated objects

are more consistent tracking, more adjustability in form of the TIME TOLERANCE parameter and enhanced expandability for possible other sensor rings as there are no time frames but a more fluid memorization of the received sensor data.

After solving the mentioned issues, we were able to obtain results for motion vectors that demonstrated a high level of similarity to the actual movement. However, it should be noted that significant noise interferences occasionally manifested, leading to erratic yet accurate findings (i.e., real direction, but incorrect velocity). Furthermore, DBSCAN occasionally causes spatially distant points to be grouped together when used in environments with a sparse number of voxels. This occurrence can be primarily attributed to the discretization from the voxel-based environment, in combination with the implementation of a density-based approach. Figure 1 clearly shows that the scanner initially detected a pool noodle as a separate object. However, when it came close to the wall, the scanner merged both into a single cluster.
par Additionally, we observed this issue when the two objects approached each other. As illustrated in Figure X, the present test involved two moving objects observed from a bird's-eye view. The initial grid (1) displays a single individual approaching the sensors at a relatively high velocity, which leads to erratic behavior. As can be seen in grid 2, the movement can be identified with a high degree of accuracy. Grid 3 illustrates the second person's approach toward the sensors. When both subjects are in proximity to the sensors, the detected objects are merged, resulting in an absence or very minimal detected motion. In grid 4, the first person exits the sensor range, and the objects separate once more. The second person's movement in Grid 5 can then be observed with more clarity until he exits the sensor range.
par In general, merging reduces our ability to separate objects by distance and therefore to detect novel items reliably as well as semantically, hence calculating the proper movement vector. Moreover, initial tests revealed that our sensor ring produces false points, which introduce noise in an already sparse voxel representation. Despite these limitations, we were able to obtain satisfactory results.

C. Classes of Limitations

Fundamentally there are two forms of limitations for our final program: Theoretical limitations which stem from the way our approach is designed and real-life limitations which mainly come from uncertainties of the used sensors.
par The system's detection capabilities are fundamentally constrained by the target's effective profile, which consists of distance, relative velocity, and material surface properties (ex.g. signal absorption in translucent materials or scattering in highly reflective ones) []. Empirical findings revealed a steep decline in detection efficacy. Low-profile geometries (e.g., 2cm diameter rods) were detectable only in immediate proximity, whereas targets exceeding a 5cm characteristic diameter (e.g., human limbs) maintained consistent detectability at ranges surpassing 100cm. Furthermore, dynamic targets demonstrated a significantly higher probability of detection compared to static counterparts. This enhancement is attributed to increased spatial sampling, as moving objects traverse multiple sensor fields of view (FOV), thereby accumulating more data points. However, deriving a precise velocity-based threshold remains challenging due to the complex correlation between varying spatial precision and signal quality across different distances.

Acknowledgment

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