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# Determining Minimal Cost of Action for Task Allocation Within Mobile Robot Swarm in Production Environments

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**Abstract.** This paper describes the continuation of a series of research in which human behavior, in the form of models and algorithms, endeavor to be mapped into the field of mobile robotics, all with the aim of more efficient path prediction with collision detection in a dynamic obstacle environment. In our latest research [1] we proposed a new approach called Sliding Holt (SH) algorithm which is used for calculation of future spatiotemporal state of dynamic obstacle. Besides SH algorithm we also proposed method for (non)collaborative collision detection with dynamic obstacles in 2D and 3D space which ensures full de-centralization of the collision detection process. Research described in this paper focuses on the application of Computer Vision for detecting the position and movement direction of mobile robots in order to create assumptions for collision detection and path planning within the production environment. We propose a new approach for detecting mobile robot direction based on triangular shape and use of Cost of Action in order to allocate tasks within robotic swarm.

**Keywords:** mobile robots, robot swarm, computer vision, collision detection, path planning, robot direction, cost of action.

## 1 Introduction

Some of the most significant discoveries of today have been made by observing natural phenomena and movements. The mechanisms that exist in nature exude harmony and precision which, even after a long and detailed observation, is not easy to model or even to understand completely. As a proof, we can mention a human who represents the most intelligent and at the same time the most complex being on Earth. The complexity of the human body is nothing special until we try to replicate in another environment or context some of the actions that a human performs with such ease and superiority. The way people make movements, path prediction, avoid static and dynamic obstacles represent particularly interesting features for the field of robotics and have been subject of much research over past decades. In order to provide modest contribution to this area, our previous research [2-4, 6, 9, 10] focused on the analysis of human behavior which

resulted in creation of adequate mathematical models and algorithms applicable in the field of mobile robotics.

A new industrial era called the 4th industry generation is completely dependent on the interconnectedness of all participants in the process and implies an enviable degree of intelligence and collaboration. This implies a symbiosis of human and robotic work environment that is completely safe, optimized in terms of eliminating unnecessary movement and loss of time, and making adequate decisions in real time.

The application of different types of sensors is an industry standard which brings a significant degree of autonomy and efficiency, especially when it comes to robot movement. As discussed in [5] pick and place, as one of the basic operations in most robotic applications, whether in industrial setups or in service robotics domains, are not easy to implement when it comes to manipulating parts with high variability or in less structured environments. These kind of picking systems only exist at laboratory level and have not reached the market due to factors such as lack of efficiency, robustness and flexibility of currently available manipulation and perception technologies. In fact, the manipulation of goods is still a potential bottleneck to achieve efficiency in the industry and the logistic market.

Parts of the system that oversee production management and accompanying processes to perform tasks in the shortest possible time need to consider energy consumption which usually means choosing the shortest path.

The movement of robots in a production environment brings multiple challenges, and one of the most important relates to determining the priority of performing tasks within a swarm of robots. If the robots were in charge of moving objects within the production or storage space, one of the possible solutions could be to assign the task of moving to the robot that is closest to the given object in terms of location. In the mentioned context, usage of holonomic or non-holonomic robots significantly determine the approach to problem solving. Namely, most of today's experimental or production implementations of robot applications, whether robots are intended for indoor or outdoor use, such as a Dispatch product called "Carry" or Seegrid GP8 vision-guided pallet truck, etc., involve the use of non-holonomic types of mobile robots.

In the next section of the paper, previous research in this area will be presented, after which the application of Computer Vision for detecting the position and movement direction of mobile robots and task allocation based on Cost of Action will be described.

## 1.1 Previous Research

Models and algorithms for collision detection in a dynamic 2D and 3D environment have been proposed in several of our previous studies [1-4, 6]. We introduced the new method of collision detection with dynamic obstacles for mobile objects space based on mathematical model of spatiotemporal de-composition of recorded motion coordinates, their respective forecast prediction using statistical methods and re-composition of future path forming metamorphous hyperspace.

Method described in [6] involves several key steps: spatiotemporal decomposition, forecast prediction using statistical methods, re-composition in metamorphous

hyperspace. The inspiration for this work came from human cognitive activities executed while single unit is moving in a group of other moving units and simultaneously detecting and avoiding collision. In majority of cases, this collision detection and avoidance is done by human objects naturally without prior high level cognitive activities which lead us to the conclusion that this model is one of the most natural way of executing these activities. Path detection of object is done in non-collaborative manner as described in previous work [1]. Main research hypothesis is that human behavior in collision detection can be described by statistical mathematical model and that given model can be expressed in form of algorithm and implemented in mobile robotics. In order to achieve requested results base research was divided into four segments. Since the proposed method considers two main operating modes: collaborative and non-collaborative, all model elements are analyzed from two different perspectives, as well as their similarities and differences.

Due to resolve the issue of creating metamorphous hyperspace, we proposed new approach called Sliding Holt algorithm [1] to calculate future spatiotemporal state of dynamic obstacle. Within first experimental phase, single exponential smoothing did not show satisfying results in extreme cases of dynamic obstacles with high coefficient of agility (even with high sampling frequencies of 1KHz). Therefore, we implemented double exponential smoothing with sliding motion coordinate records in which we propose discarding of old data before motion vector alteration occurs.

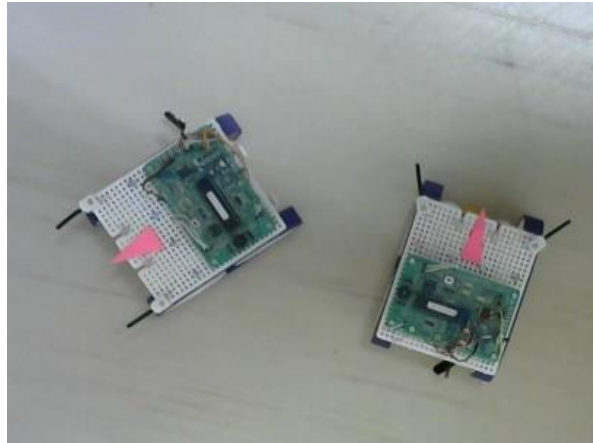
## 2 Computer Vision Based Location and Direction Detection

As discussed in [8] robots in the industrial sector have evolved from powerful, stationary machines into sophisticated, mobile platforms to address a broader range of automation needs. Autonomous mobile robots utilize feedback from sensors to navigate their environment. State of the art mobile robots has an envious level of intelligence and are able to detect obstacles present on their path and recalculate a route around the obstacle to get it to its destination. Nevertheless, the real environment brings with it a multitude of cases that have not yet been adequately researched in terms of the existence of models and / or algorithms for solving them.

Previous research [7] described universal experimental environment for algorithm testing in the field of mobile robotics which is appropriate for tracking, collision detection and avoidance, and path planning. In order to provide precise positioning and direction detection, we proposed two-color markers which are positioned on the top of mobile robot. The initial experiment with single color marker showed low level motion path stability in the sense that it was unclear in which direction mobile object is moving. With the addition of second color marker, it became clear what is front and what is rear of the object, thus enabling straightforward definition of motion vector direction.

Although the use of two-color markers gave satisfactory results, continued research revealed some disadvantages. The main disadvantage relates to the need for fine tuning of colors and the sensitivity of the detection process to the intensity of ambient light. In order to eliminate the mentioned disadvantage, in this paper we proposed the

implementation of shape detection using a triangular marker of any color. **Fig. 1.** shows the experimental environment in which the use of triangular markers was tested. The figure illustrates a part of an application that uses the Computer Vision OpenCV library to capture a video stream that will be processed and used to detect the location and direction of the robots.



**Fig. 1.** Picture from video stream with indicated triangular markers

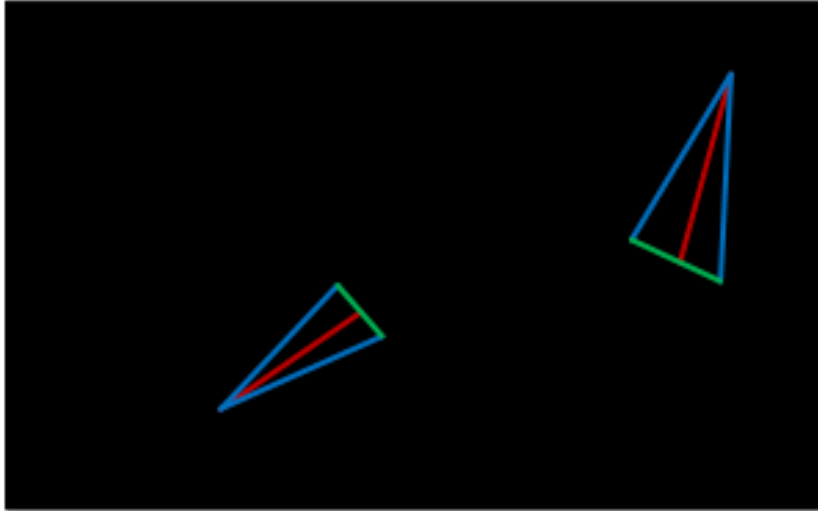
Processing an image from a video stream involves several stages that are described within the following pseudocode.

```

listOfContours = DetectContours(stream)
foreach(contour in listOfContours)
  if (contour == triangle)
    (shortestLine, frontPoint) = AnalyzeShape(triangle)
    contour.Tail.X = (shortestLine.Begin.X + shortestLine.End.X) / 2
    contour.Tail.Y = (shortestLine.Begin.Y + shortestLine.End.Y) / 2
    contour.Front.X = frontPoint.X
    contour.Front.Y = frontPoint.Y
    DrawLine (shortestLine, color : green)
    DrawLine (contour.Tail, contour.Front, color : red)
    listOfTriangles.Add(contour)
  
```

The first phase in processing involves the detection of all shapes followed by their analysis. If the shape has a triangular form, then a more detailed analysis is performed, within which the shortest side and its corresponding points are identified. The remaining, third point is declared as the front point of the robot. Subsequently, the absolute mean between the points on the shortest line is calculated, which determines their position on the X and Y axes, and it becomes the rear point. The mentioned calculations

created a precondition for plotting the location and orientation of the robots detected on the stream as indicated on **Fig. 2**.



**Fig. 2.** Detection of robot's position and direction

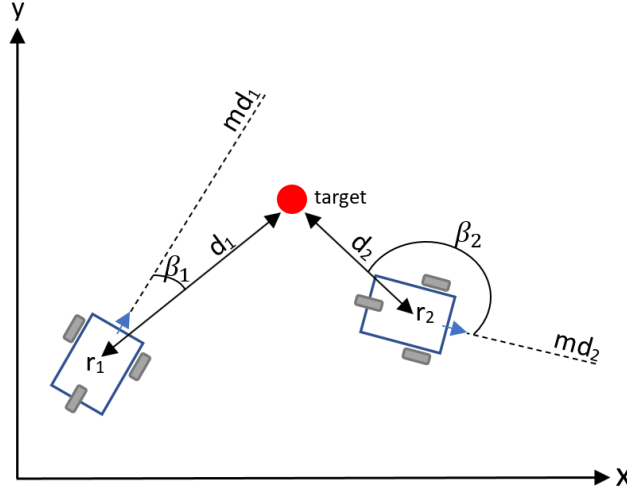
By applying Computer Vision and defined processing phases, we can detect the location and direction of all members of the robot swarm which have been identified in the video stream. After detecting them, it is necessary to define a model for assigning tasks (e.g., moving a certain object from one location to another) with maximum degree of efficiency, which means determining the Cost of Action (CoA) for each of the detected/available robots.

### 3 Cost of Action

Within this chapter, the result of initial research in the field of implementation of more efficient distribution of tasks in a swarm of robots is presented. Namely, assigning tasks to non-holonomic robots requires an analysis of several factors, not just the absolute distance from its current position to the defined location (e.g., target). The autonomous movement of non-holonomic mobile robots will very often lead to a case in which the task of moving a certain object will be assigned to a more distant robot. As shown in **Fig. 3**, the robot  $r_1$  is further away from the object (e.g., target) in relation to the robot  $r_2$  (i.e.,  $d_1 > d_2$ ) but the angle (i.e.,  $\beta_1$ ) between the shortest distance (i.e.,  $d_1$ ) to the destination and the movement direction (i.e.,  $md_1$ ) of the robot  $r_1$  is much smaller than the angle between the shortest distance (i.e.,  $d_2$ ) to the destination and the movement direction (i.e.,  $md_2$ ) of the robot  $r_2$ .

Considering the aforementioned, it can be concluded that a higher value of the angle  $\beta$  will lead to a higher Cost of Action in terms of required energy (battery consumption),

time to execute the action (ignoring the need to wait to avoid collisions with static or dynamic obstacles), energy caused by friction, current state of motion etc.



**Fig. 3.** Parameters used to determine Cost of Action in task allocation process

Analyzing the case in which the mobile robot has the possibility of free rotation (caster wheel or tracks), in order to calculate the CoA for the robot  $r$  to reach from the current to the target location, the following calculation was used:

$$CoA_r = \frac{d}{v} + \frac{\beta}{\omega} \quad (1)$$

$CoA_r$  – Cost of Action that robot  $r$  needs to reach the target location

$d$  – distance to target location

$v$  – linear velocity

$\beta$  – angle between orientation and target direction

$\omega$  – angle velocity

$$\minCostOfAction = \min ([CoA_{r_1}, CoA_{r_2}, \dots, CoA_{r_n}]) \quad (2)$$

The current experimental environment is a special case of a general concept in which the CoA per unit of time for each mobile robot is identical. This implies that all robots within the production environment have identical technical characteristics meaning identical weight, battery life, vehicle frame, friction of the drive mechanism against the ground, etc. To assign a task, it is necessary to calculate  $CoA_r$ , which, in this case, represents time to reach the target, for each unallocated/idle mobile robot. The task will



be assigned to the robot for which the lowest CoA value (`minCostOfAction`) was calculated. Taking into account the fact that the current research considered only time, in future research, a general case will be analyzed, which implies the existence of an unstructured environment with mobile robots of different technical performance.

## 4 Conclusion

Efficient management of production environments is a goal that is not easy to achieve. However, some of the basic prerequisites are certainly the interconnection between all participants in the production process, the application of autonomous robots that will coexist with humans within a secure work environment, maximum utilization of all resources and elimination of unnecessary actions or waiting. The movement of autonomous robots in a production facilitates the management of such environments, but it is also necessary to provide a systematic environment that will allow smooth movement and efficient assignment of tasks (e.g., moving a particular object from one location to another). In this paper, we have proposed a new approach for detecting the location and direction of a mobile robot, and calculation of Cost of Action in order to select the most appropriate robot for the task.

Future research will be focused on the introduction of new parameters such as: battery status, speed of the mobile robot (which refers to the energy needed to overcome inertia), the necessity to wait for certain actions (e.g., making turn or alter velocity) in order to avoid collisions etc.

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