24-070

Perceptive Track Projection—Creating Context Sensitive Path, Velocity, and Auxiliary Activity Projections for Use in Autonomous Safety Intervention Systems

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ABSTRACT

Machine Situational Awareness (MSA) requires the ability to efficiently evaluate the probability of interaction of objects within the environment, without creating false alarms or ignoring materializing hazards. To do this, an MSA system needs to assign context to observed object activity and integrate as much information about object identity, kinematics, behavior, and current state as possible. This paper describes how known object characteristics, attributes, and activities (drilling, dumping, driving, etc.) can refine interaction probabilities and help identify rogue actors that introduce anomalous risks to the health and safety of miners. Path projections need to incorporate velocity and direction as a function of time while accounting for terrain, safety response, environmental factors, current assigned activity, etc. This paper also describes the methodology for properly prioritizing responses to place the highest value on human safety.

MACHINE SITUATIONAL AWARENESS (MSA)

The ISO 17757 [1] refers to situational awareness (SA) as an overall concept of humans and highly automated / autonomous (A/A) equipment working together. The standard covers many considerations for human factors and roles in situational awareness. While there has been a great deal of study and development on the human side of this structure, the equipment contribution is in its infancy. Given the absence of a formal definition, we found that the existing terminology fell short in effectively expressing the essence of our work. As a result, we introduced the term "machine situational awareness," which encapsulates the equipment's capacity to perceive its surroundings, assess potential interactions within that context, and recognize both existing and emerging hazards.

Humans have the innate ability to constantly evaluate their environment and make millions of risk-reduction decisions a day (some trivial, some lifesaving). The downside is that humans lose focus for a myriad of reasons such as fatigue, boredom, distraction, etc. [2]. Machines equipped with safety intervention controllers (parallel to machine control) that employ MSA can potentially perform these same functions without the shortcomings of humans, but they will have to be nearly infallible to be trusted to operate in the presence of humans. Some events are tolerable in a human-controlled environment that would not be in an autonomous world (requiring mines to build new exclusion zones, etc.). For a number of reasons, the expectation for equipment far exceeds that of humans [3]. Within that paradigm, MSA must be substantially more robust than humans. There are three critical elements to MSA, a) redundant, consistent, and reliable perception of objects (mobile and stationary) in the environment, b) realistic, deterministic, and comprehensive projection of the paths and activities those objects will have as a function of time (including probability fields), and c) rapid, meaningful evaluation of projected interactions in expected and alternate futures. This paper focuses on the second element—Path Projection.

PATH PROJECTION

Path projection is a prediction of the motion and behavior of an object, with corresponding confidence (inverse of variance) in that prediction. In its simplest form, track projection would project the position and velocity of a projectile influenced only by gravity and air friction. In more practical applications, it would project the position, velocity, orientation, and auxiliary activity (dumping, spraying, drilling, etc.) of a piece of mobile equipment as a function of time. The associated time horizon depends on what time the equipment requires to intervene on behalf of safety. This projection is not simply dynamics and kinematics, it is heavily dependent on the context of an object's motion and state. Some contributors to context are external physics (road conditions, weather conditions, slope, curvature, etc.), internal physics (braking and acceleration ability, turning potential, center of gravity, weight, etc.), current activity (driving, dumping, drilling, waiting, etc.), expected behavior (road follower, typical speed versus. slope, etc.), and intent (change tasks, destination, changing speed, etc.). Each of these contexts contribute to the calculation of projected path and associated variance (inverse of confidence).

For MSA to work, the perception engine needs to pass on object identification (what is it), current location (where it is) and a profile of current direction and speed (where it's heading), and the current activity context (what it's doing). Most equipment on a mine site is distinct and known as opposed to automotive environment. This enables recognition of a discrete set of objects that are well known and relatively understood and predictable (baseline behavior and capabilities). On a mine site, the MSA system would have a database of the characteristics of all the equipment types in its environment.

Introducing Context

Utilizing context is fundamentally a function that adjusts the calculation based on the current state. Context can change a set of conditions and/or applicable algorithms, or it can adjust the parameters and coefficients of dynamic and kinematic calculations. When making decisions about what context to include in MSA, anything that can materially affect the action of an object must be modeled. Objects are anything in the environment that an MSA equipped machine can interact with (pickup trucks, people, boulders, other equipment, etc.). Machines can also interact with features of the environment such as berms, slopes, edges, roads, etc.), but the topography is typically static, at least in the short term. For an example, road condition is a context that can affect how the machine will interact with the environment (stopping distance, turn radius, maximum safe speed, etc.).

EXTENSION TO PERCEPTION

The human parallel to Path Projection in an MSA system is the way we subconsciously calculate what movements will be made by objects in our immediate world and evaluate choices to avoid an incident. We do this while driving, walking down a street, pushing a shopping cart, playing sports, and virtually every task in which we engage involving movement. We usually do not have conscious thoughts about what we are doing. It is just automatic. The goal of this project is to develop an approach that emulates that ability by harnessing modern sensor technology, advances in computing potential, and emergence of new mathematical strategies that make this within reach.

Path projection must take all we know about objects or environmental features and create a best guess about what will happen in the near future and relay the level of confidence in that projection. It must tolerate sensor inaccuracies, lag times, conflicting data, environmental influences, object behavior and characteristics, etc. It must evaluate the probability profile surrounding it and other objects. This is all because any safety intervention system cannot have false trips or anomalous responses. The gateway to industry acceptance is that the system perform better than a human would in preventing unwanted interactions [3].

To have adequate information to model a path more than a couple seconds into the future, mathematics would need to accommodate position and 3 derivatives: speed, acceleration, and jerk [4]. The system would also need to calculate the variance for position as a function of time. That variance would include anything in the system or environment that would contribute to inaccuracy (e.g., sensor input) or path deviation (e.g., sudden change in object acceleration or direction). Given position variance handed from the perception engine, the path model must be smoothed using a 4th order (to model jerk) curve fit. Whatever model is used, it must also produce variances for each variable it is reporting. This would typically be derived from the co-variance matrix that is derived during matrix calculation.

Different object types would require different motion models. For instance, wheeled vehicles are controlled via a set of steering tires and thus must be modeled as such. A human, on the other hand, can change directions and speeds very quickly and are erratic and indeterminate by comparison, requiring a different motion model. The Path Projection system uses the motion model associated with the identified object type passed from the perception module. Each motion model must accommodate all the relevant contexts that are identified for that object. In a mine environment, the number and type of objects are known and limited (unlike the automotive world). Contexts and associated motion models would need to be provided with the equipment at purchase time, developed by third party vendors, or created by the mine personnel.

Wheeled Vehicle Motion

Wheeled vehicles have the physics that motion in the direction of travel (velocity) is regulated by torque to the wheels, and turning (angular velocity) is controlled by the angle of the steering wheels. There are exceptions to this when linear and angular forces exceed what the surface will support (wet roads, etc.). In general, linear and angular position with three levels of derivative (velocity, acceleration, and jerk) coupled with context is sufficient information to project a few seconds into the future. An additional complexity is the requirement that confidence be integral to the project position and velocity as a function of time. Following is an option for the math model that could be incorporated for this task.

Model Structure

Using standard polynomial equations for position and rotation, as well as modeling the way they interact with each other, is a sound approach to creating elements for a matrix solution system that will calculate projected state as well as a covariance matrix that gives uncertainty for any data point as a function of time. In reality, impact probability is determined by proximity and variance at some point in time, while severity of the interaction is a function of velocity (speed and direction). MSA must complete that projection for the "real" case (current truth) and also for potentially thousands of alternate states being evaluated by the Probability Processing Engine within the scan cycle time of the perception system.

For polynomial displacement function, the basic model would look like:

$$s = s_0 + \Delta t\left(\frac{ds}{dt} + \frac{1d^2 s}{2dt^2} + \frac{1d^s s}{6dt^3}\right)$$

And for the angular function:

$$\theta = \theta_0 + \Delta t\left(\frac{d\theta}{dt} + \frac{1d^2\theta}{2dt^2} + \frac{1d^3\theta}{6dt^3}\right)$$

where:

s = distance along the curve of travel
θ = angular position of the vehicle
t = time

Human Motion

Humans have inertia but are relatively indeterminant and unconstrained in motion. Therefore, there is a significant variance associated with any motion model representing humans in any environment in which they are free to move. Human kinematics is vastly more complicated than that of wheeled or tracked equipment. All this leads to the need for a robustly comprehensive model and limited confidence of future location. This, coupled with extreme valuation of life and health, forces any Assured Autonomy Safety Intervention System (AASIS) to automatically provide wide berth between humans and any operating autonomous equipment.

There has been much research into human motion models (ref) that incorporate predictive behavior based on limb segment motion for path projection at close range (close enough for perception to discriminate limb segment position) and more general motion at a distance (>50 m). These are expensive algorithms in terms of computing resources, but also the most important because safety of humans is of primary concern.

Stationary Equipment

Stationary equipment like conveyors, crushers, etc. present significant hazards to operators because they have moving parts, elevated surfaces, electricity, hot surfaces, and other characteristics that can be hazardous. Each hazard has an associated mechanism of injury and a field of danger that can be modeled with affiliated context. This field is not binary (a hard line within which danger exists), rather it typically possesses a statistical distribution of danger that is often context dependent. An example of this would be an open electrical panel. It is only dangerous when it is energized. In this paradigm, an AASIS equipment monitor would typically be modeling human movement within context driven fields of danger that can trigger intervention responses like sensory warning (auditory, visual, tactile, etc.), change of state (slow or stop motion, lock a gate, remove power, etc.), or any other action that the machine can control that would reduce the project risk of a human's actions.

Hybrid Equipment

Hybrid equipment is both mobile and stationary (rock drill's, etc.). In stationary mode, stationary equipment often possesses articulating components that present hazards to operators and maintenance personnel. This presents a hierarchy of context that would select one motion model for stationary mode and another for mobile operation.

Human-operated Equipment

Human-operated equipment has the kinematic constraints associated with the machine (service vehicles, water truck, grader, etc.), and the relative indeterminacy of humans. The motion model would be the same as autonomous, but context would add large variances to accommodate the unknown intent of the driver. The value of this object would reflect the fact that there is an indispensable human on board. This, coupled with the large variance, would automatically cause AASIS-enabled equipment to provide wide berth and slow operation in the presence of human-operated equipment.

SUMMARY

In order to sufficiently model multiple object motions for an MSA system, there needs to be object type specific motion models and a good understanding of all the contexts of motion for each type. Creating a Path Projection engine for MSA starts with a catalogue of expected types, and all the things that change their behavior. Each type will also need a motion model appropriate for its particular kinematics and a clear understanding of how contexts will influence the motion. Each motion model must be able to calculate associated statistical variance as a function of future time. The probability processing engine will use this information to evaluate likelihoods and costs of interaction for each pair of objects identified. Ultimate safety of an AASIS system is heavily dependent on the quality of data provided by Perception and the adequacy of modeling created in Path Projection.

Autonomy is an expensive and complicated endeavor that is focused on radical improvements in safety and productivity. MSA is a crucial enabling element for the transition from where the mining industry is now to where it is going. SMRD/NIOSH (Spokane Mining Research Division of the National Institute for Occupational Safety and Health) is actively working to identify sensor suites, software tools, mathematical models, and other emerging technologies that will help the industry coalesce around a common, determinant, robust, flexible MSA framework that will usher in the next generation of safety and productivity by incorporating the AASIS architype.

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24-071

Practical Application of Surfactants for Respirable Silica Dust Control

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ABSTRACT

Respirable crystalline silica poses a significant health risk, with the American Lung Association estimating that 2.3 million workers are exposed to silica in the workplace. This includes mine workers as well as those in many other industries. Reducing dust formation is sometimes not possible so other methods to reduce exposure are critical. These methods include the use of surfactants to reduce airborne dust particles. However, it is the proper selection and application of surfactants that leads to reduced dust exposure. A discussion of how surfactants work, especially for silica dust, leads to guidance for surfactant selection followed by a review of technologies for their application.

INTRODUCTION

Respirable crystalline silica has been studied as a potential carcinogen in dusts from many sources, including those produced in mines. Whether mining specifically for silica or mining other minerals, it is likely that silica is in the mined product as it is an accessory mineral phase in many common commodities as indicated in Table 1 (1). While coal is not on the list, it is certainly well known that coal also contains quartz, with a 1990 US Bureau of Mine work, Sources and Characteristics of Quartz Dust in Coal Mines, initiating some of the research on silica in coal (2).

Researchers have also indicated that quartz cannot be treated as a single mineral phase as there are many variations in contaminants and associated minerals (see, for example, 3, 4, 5). In general, however, it appears that the issue with crystalline silica, most notably α-quartz, is the formation of reactive oxygen species (ROS) on the surface of dust particles, forming "silanols" that interact with lung tissue to cause fibrosis and lung cancer (3, 4, 5). These works and others along with the increase in the occupational respiratory diseases silicosis and coal worker's pneumoconiosis (6, 7, 8, 9) spawned new research, including recent international papers by Azam et al. (10), LaBranche et al. (11), and Li et al. (12). These and many other papers document research regarding respirable dust and, especially, silica dust. As this paper takes a practical look at surfactants for respirable silica dust, this is not the place to document these many papers, though Arnold and her team have a review paper in progress. Suffice it to say that respirable silica dust and its toxicity is the subject of many current National Institute of Occupational Safety and Health (NIOSH) studies (13).

In addition, it is important to note that the US Mine Safety and Health Administration has put forth new silica dust regulations for comment (14). The use of surfactants to control dust and, especially, silica dust, is a timely topic to review.