Source detection of atmospheric releases using symbolic machine learning classification and remote sensing

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When an airborne toxic contaminant is released into the atmosphere it is rapidly transported by the wind and dispersed by atmospheric turbulence. Within a few days, contaminant clouds can travel thousands of kilometers and cover thousands of square kilometers. If the nature of the material released is hazardous, a large population can be affected with serious and long term consequences within a very short period of time. Potential atmospheric hazards include toxic industrial chemical spills, forest fires, natural gas releases, intentional or accidental releases of chemical and biological agents, and radiological material. Rapid identification of the nature and source of the contamination is critical to effective emergency response, consequence management, and restoration activities.

The problem of source detection of atmospheric releases is a challenging scientific problem. There are currently no established methodologies for its satisfactory solution, and there is a great degree of uncertainty towards the effectiveness and applicability of existing techniques. At present, the nature and source of atmospheric hazard releases must be inferred from the anomalous levels of contaminant concentration measured by sensors on the ground or by satellite-borne remote sensors. Our approach uses a combination of evolutionary algorithms and machine learning rule induction. Unlike traditional Darwinian evolutionary algorithms, which generate solutions through a pseudo-random search process, in our proposed approach, the values of the variables are not randomly assigned, but they are set according to the rules discovered by a machine learning program.

The evolutionary process starts with the generation of random candidate solutions within the boundaries of the search space. Each of the solutions is evaluated according to an error function defined by the match between forward atmospheric dispersion simulations and the concentrations observed through ground sensors or satellites. At each step, the best and worst performing solutions are clustered into HIGH and LOW groups respectively. These are then used as examples and counter-examples for the machine learning rule induction algorithm. The learned rules identify the subsections of the multi-dimensional search space which are most likely to contain optimal solutions. New examples are instantiated within the new search boundaries, and evaluated according to the error function. The evolutionary process continues until a termination condition is met.

Central to this algorithm is the matching of the candidate solutions with the observed values. The National Polar-orbiting Operational Environmental Satellite System (NPOESS) is the next generation of earth observation satellites, replacing the Defense Meteorological Satellite System and the POES (Polar-orbiting Operational Environmental Satellite) vehicles. NPOESS is planned to be a four vehicle, multiple sensor system. This system will provide greater temporal, spatial, and spectral resolution in comparison to the current fleet of environmental sensor systems. This increased resolution will assist in the detection of concentration clouds and provide more accurate insight into the observed values. NPOESS provides a unique and valuable addition to our ability to discretely detect atmospheric releases by providing more accurate information concerning the meteorological conditions that are input into the mesoscale meteorological model for the numerical simulations of the transport and dispersion of the pollutants.

Our intention is to demonstrate the effectiveness of this technique in determining the source of atmospheric contaminants and the increase in precision provided by the next generation of environmental satellites.

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