VIRAL INFECTION PROPAGATION THROUGH AIR TRAVEL

Ashok Srinivasan, Florida State University
Sirish Namilae, Embry-Riddle Aeronautical University
Anuj Mubayi, Arizona State University
Robert Pahle, Arizona State University
Matthew Scotch, Arizona State University

www.cs.fsu.edu/vipra
OUTLINE

• Introduction
• Prior Results
• Recent Infection Propagation Results
• Conclusions
INTRODUCTION
MOTIVATION

• Air travel is an important factor in the spread of infections

• There had been calls to ban flights from Ebola infected areas
  • This can have large human and economic impact
  • Fine-tuned policy prescriptions can be as effective
    • Reassures the public that action is being taken
    • Avoids negative human and economic impacts
PROJECT GOALS

- Develop models and decision support tools to help analyze impact of policy decisions on spread of diseases through air-travel
  - Will provide insight to decision makers on consequences of policy or procedural choices
  - Original work focused on Ebola
    - Current work includes other diseases
CURRENT MODELS

• Typically focused on scientific understanding, rather than policy analysis
  • Predictions are difficulty due to inherent uncertainties
• Usually at an aggregate level, which makes evaluation of impact of new policies difficult
• Inaccurate predictions on Ebola
  • Predicted millions infected by early 2015 and hundreds of thousands dead
OUR MODELING APPROACH

• Use fine-scale model of human movement in planes to determine response to policies
• Link with phylogeography model to examine global consequences
• Parameterize sources of uncertainty
  • Parameter sweep over this space to identify vulnerability
• Validate with similar diseases
Air-travel policies to reduce infection spread

- Airport layout
- On-ground procedures
- Boarding and deplaning
- In-flight procedures

Validation and model refinement

Phylogeography global model

Number of contacts

Susceptible – infective stochastic model

Human movement in flights and airports

% Probability of Infection

Days post onset of symptoms

# infected per airport

Probability of Infection

Phylogeography global model
QUESTIONS TO BE ANSWERED

• How high a risk does air-travel pose in spreading a disease outside its source countries?
• Can simple policies reduce infection risk without causing major disruptions?
  • Change plane type
  • Change boarding and disembarkation procedures
  • Change seating arrangements
  • Airport layout and procedures
PRIOR RESULTS
SELF PROPELLED ENTITY DYNAMICS MODEL

- Social dynamics is based on the idea of Molecular Dynamics, with each entity treated as a particle
  - Individuals experience self propulsion that induces them to move toward their desired goal
  - They experience repulsive forces from other persons and surfaces
- We add human behavioral characteristics to social dynamics

Flowchart:
- Initialise
  - Self propelling desired velocity
    - Calculate interparticle forces
      - Integrate for motion
        - Calculate contacts
EXAMPLE OF UNCERTAINTY: PEDESTRIAN SPEED

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Slow</th>
<th>Ordinary</th>
<th>Fast</th>
<th>Running</th>
<th>Sprinting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>21–30</td>
<td>0.7–1.4</td>
<td>1.1–1.6</td>
<td>1.5–2.0</td>
<td>2.0–3.6</td>
<td>3.6–5.2</td>
</tr>
<tr>
<td></td>
<td>31–40</td>
<td>0.8–1.3</td>
<td>1.1–1.5</td>
<td>1.5–2.1</td>
<td>2.0–3.7</td>
<td>3.9–4.5</td>
</tr>
<tr>
<td></td>
<td>41–50</td>
<td>0.7–1.3</td>
<td>1.1–1.6</td>
<td>1.5–2.0</td>
<td>2.4–3.0</td>
<td>3.0–4.2</td>
</tr>
<tr>
<td></td>
<td>51–60</td>
<td>0.7–1.1</td>
<td>1.1–1.6</td>
<td>1.6–2.1</td>
<td>2.0–3.6</td>
<td>2.9–4.3</td>
</tr>
<tr>
<td>Male</td>
<td>21–30</td>
<td>0.8–1.4</td>
<td>1.3–1.6</td>
<td>1.8–2.2</td>
<td>2.6–4.6</td>
<td>4.3–6.6</td>
</tr>
<tr>
<td></td>
<td>31–40</td>
<td>1.0–1.4</td>
<td>1.2–1.8</td>
<td>1.8–2.5</td>
<td>2.8–4.6</td>
<td>4.8–6.9</td>
</tr>
<tr>
<td></td>
<td>41–50</td>
<td>0.8–1.3</td>
<td>1.2–1.6</td>
<td>1.8–2.3</td>
<td>3.0–4.2</td>
<td>4.3–6.9</td>
</tr>
<tr>
<td></td>
<td>51–60</td>
<td>1.0–1.3</td>
<td>1.3–1.6</td>
<td>1.8–2.1</td>
<td>2.6–4.2</td>
<td>5.0–5.7</td>
</tr>
</tbody>
</table>

• Choose parameter combinations that reflect real behavior
• Select a variety of distinct scenarios
A320 144 Seats Boarding
• Include some validation with the simulation
• Basic sequential optimization
• The above two improve performance by an order of magnitude on 1331 cores
IO optimization on 68921 cores of Blue Waters led to factor 2 decrease in wall clock time
PERFORMANCE WITH LOAD BALANCING

- Time with 68921 parameters using 39655 cores
RECENT INFECTION PROPAGATION RESULTS
INFECTION TRANSMISSION

Since $R_0$ for Ebola is around 2, that means a typical infective individual will produce on average two new secondary cases thus, replacing him or herself, producing an additional case, and eventually leading to a large outbreak in the population.

- Probability of infection transmission modeled as a function of distance to infected person, exposure time, and infectivity.

http://sploid.gizmodo.com/ebola-spreading-rate-compared-to-other-diseases-visuali-1642364575
DETERMINING INFECTION PROBABILITY

- Blood virus content used to estimate infectivity probability

Data source: Centers for Disease Control and Prevention
IMPLICIT OF BOARDING STRATEGIES

- Boarding Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
  - Contact radius = 1.2 m
- Strategies that prevent clustering in the cabin reduce infection likelihood
IMPACT OF DEPLANING STRATEGIES

- Deplaning Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
  - Contact radius = 1.2 m
- Less important than boarding in infection spread
IMPACT OF INFECTIVITY

• Boarding + deplaning Boeing 757-200
  - One infected passenger
  - Infection probability varies in (0, 0.6]
  - Contact radius = 1.2 m
IMPACT OF PLANE SIZE

- Boarding Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
  - Contact radius = 1.2 m
IMPACT OF CONTACT RADIUS

- Boarding + deplaning Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
- Particle size 0.1-10µm
  - Distance traveled up to 2 m
  - Long Distance: Small particles (aerosols) – SARS, H1N1
  - Short distance: Coarse droplets – Ebola
LONG VS SHORT CONTACT RADIUS

- Infection contact radius
  - Ebola: 1.2 m
  - SARS: 2.1 m
- Model includes airport gates
CONCLUSIONS
SUMMARY OF COMPUTATIONAL OPTIMIZATIONS

• Factor 10 improvement in performance through optimization

• Dynamic load balancing increases efficiency from ~50% to ~90%
  • Post-priori bound shows it is within 10% of optimum in time taken for the number of cores used

• Better run time prediction will permit more efficient parallelization
  • Can reduce cores used further
  • Almost optimum static load balancing
SUMMARY OF APPLICATION RESULTS

- Identified procedures that can lead to significant decrease in contacts
  - Random boarding leads to lower risk of infection spread
  - Boarding has a higher impact than deplaning
  - Smaller planes are better than larger ones

This material is based upon work supported by the National Science ACI under grants #1525061, #1524972, and #1525012 on Simulation-Based Policy Analysis to Reduce Ebola Transmission Risk in Air Travel and PRAC grant on Petascale Simulation of Viral Infection Propagation through Air Travel. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. We thank NCSA for providing use of the Blue Waters supercomputer.
FUTURE DIRECTIONS

• Extend this approach
  • Other disease: Flu, measles, SARS, etc
  • Include infection spread in airports

• Improve computational efficiency
  • Better time prediction
  • More efficient parameter sweep

• Eventual goal is simulation time ~ 1 minute
  • Requires finer grained parallelization