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A Computational Framework for Determination and Exploitation of Social Network Models from Wide-Area Persistent Surveillance Imagery

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Statement of Problem

Wide-area persistent surveillance promises to revolutionize domestic situational awareness by providing real-time visual imagery of events, individual actors, and groups of interest to the national homeland security mission. However, fully realizing the potential of this technology requires computational tools capable of extracting actionable information from many highly dense data streams. At present, analysis of persistent surveillance imagery demands significant time and manpower resources as intelligence analysts tediously examine such data to identify suspicious activity. With the granularization of homeland security threats, the current approach and its associated strain on human resources must be reexamined with an eye towards automation. In order to realize the promise underlying wide-area persistent surveillance technology, an interdisciplinary approach is necessary. This brief argues that by merging analytic tools from the normally disparate fields of behavioral science and engineering systems theory, a methodology for automatic target identification and exploitation can be realized.

Background

Situational awareness though video imagery has a long history as a deterrence mechanism, and recent military development has established persistent surveillance imagery as a revolutionary intelligence collection tool. In addition, persistent surveillance presently is used for many domestic security applications, such as situational awareness for public events, border and port monitoring, and law enforcement. Wide area persistent surveillance typically collects video imagery with sensors onboard unmanned aerial vehicles (UAVs) such as the Predator, Global Hawk, Reaper, and Liberty, although a variety of different platforms—including satellites, near-space vehicles, manned aircraft, and ground-based emplacements—are also used. The most recent versions of this technology allow for the continuous remote observation of all public motion in towns as large as 1 square mile, with the promise of extension in the near future to towns of up to 3 square miles in size (Barnes, 2009).

The integrated sensors within persistent surveillance platforms are also becoming increasingly sophisticated. For example, biometric systems capable of identifying a moving subject's iris have been demonstrated (Sarnoff, 2009). Predictive computational algorithms for automatically tracking targets in persistent surveillance imagery are a major research effort. Currently, this is achieved by such methods as temporal differencing, background subtraction, and optical flow resolution algorithms of varying complexity (Collins Lipton, Fujiyoshi, & Kanade, 2001; Adams, 2008). Temporal differencing is accomplished by determining which pixels "move" from time period to time period, thereby identifying moving objects. Background subtraction involves removing environmental imagery and identifying the non-background units as moving objects. Optical flow is useful in certain situations because it can accurately identify target motion in the presence of camera motion. Development of adaptable dual-integrated surveillance/sensor systems (Yao et al., 2010) is an area of continuing research. Finally, the recent development of an epidemiological surveillance system for real-time population health monitoring in the state of Massachusetts (Reis et al., 2007) indicates that situational awareness provided by visual imagery, in conjunction with non-visual metrics of interest (e.g., financial transactions), is headed toward very large-scale integration.

Extracting social network diagrams from persistent surveillance data is another area of strong interest. However, techniques for describing social network dynamics are extremely varied and complex. In the past, social modeling focused on distinctions among three methodological approaches: statistics, formal mathematics, and computer-based simulation.[1]

[1] For a concise overview of the history of social computing, particularly its increasing scope and complexity, see Wang, Carley, Zeng, and Mao (2007).

The contemporary instantiation of social network analysis uses software to build models reliant on statistics for prediction (Wasserman & Faust, 1994; Wasserman & Pattison, 1996; Huisman & van Duijn, 2005; Knoke & Yang, 2008). Specific tools, such as particular statistical (e.g., Bayesian updating) or computing (e.g., genetic algorithms) techniques (Gill & Swartz, 2004; Mitchell, 1996) have been used, but the number of techniques has become so great that even experts are unable to maintain awareness of their introductions, iterations, and evolutions.

A fruitful way to think about types of models of social behavior is to consider a model's *ambition* and its *primary unit of analysis*.[2] "Ambition" refers to what the model has set out to accomplish: Is the researcher trying to use the model to predict human behavior or to establish a baseline for comparison? In other words, is the model intended to demonstrate how people actually behave, or to develop an analytic tool? The former is consistent with many endeavors, ranging from management science (Boudreau, 2004) to marketing (Goss, 1995) to intercepting an enemy on a battlefield (Epstein, 1997) to studying traffic patterns (Herman, 1992) to epidemiology (Nuckols, Ward, & Jarup, 2004). Most of these applications focus on using historical data to generate models of future behavior and do not operate in real time. Recent scholarship has successfully automated the analysis of multi-sensory data to predict social behavior, thus demonstrating a way forward for real-time prediction (Wyatt, Choudhury, Bilmes, & Kitts, 2008; Choudhury, Philipose, Wyatt, & Lester, 2006).

The latter approach, deduction, approximates "proper" behavior given a set of starting conditions. Real-world data may then be compared to the model, and discrepancies offer an opportunity for new research endeavors. Deductive models, most often associated with game theory and other formal mathematics, have been famously applied to such social behavior as voting patterns and collective action (Downs, 1957; Olson, 1965). One popular application of this kind of modeling is scenario-based analysis (such as estimating the effect of government policy on criminal behavior) as a decision-making tool (Liu & Eck, 2008).

The second defining characteristic of a social model is its unit of analysis. All behavioral models are to some degree designed to explain overall properties of a social system; this has most explicitly been the case following the development of complexity theory in the 1980s and 1990s (Waldrop, 1992). Researchers drawing on the science of complexity have focused on the concept of *emergence*, or the tendency for complex adaptive systems to produce aggregate behavior that is different from the behavior of each of its constituent parts (Holland, 1998; Holland, 1992; Gell-Mann, 1995). The relevant question for differentiating between models is the level of analysis that a given model emphasizes in seeking to explain the overall properties of the social system under examination.

[2] For alternative approaches to describing the state of modeling social behavior during the past 20 years, see Liu, Salerno, and Young (2009); De Marchi (2005); Liebrand, Nowak, and Hegselmann (1998); and Hanneman (1988). The Liu, Nowak, and Hegselmann volume demonstrates the vast array of subject matter and techniques that fall under the heading of "social computing and behavioral modeling."

The most common division is between models focused on the behavior of individual *agents* (which may refer to an individual person or cluster of persons) and those that emphasize the *structure* of interactions between agents. Models focusing on the individual level of analysis emphasize the "rules" governing each agent's behavior (e.g., preferences, constraints) and seek to understand why an overall outcome results from multiple agents' interactions with one another. Individual-oriented models may be either deductive or focused on prediction; for example, game theory or other rational choice models are deductive, while agent-based models may be either deductive or focused on real-time prediction (Epstein, 2007; Lustick & Miodownik, 2009; Lustick, Miodownik, & Eidelson, 2004).

Structural models, on the other hand, focus on the types of relationships between individuals (e.g., communication, access to information) and how those relationships in turn produce emergent properties of the social system. Network analysis is the most common type of structural model that may operate in real time. While network models are often two-tiered (in that rules govern the properties of individuals), the most consequential level of analysis is usually considered to be the structure of the network (Wasserman & Faust, 1994). Recent work of interest to the national security community has further developed two-tiered models by adding multiple types of agents to complex social network models (Carley, 2002). An example of deductive structural modeling is rational choice institutionalism; this approach seeks to explain how social structures (e.g., power relationships, law, pecuniary incentives) shape the behavior of agents (Shepsle, 1989; Hall & Taylor, 1996).

A system of persistent surveillance seeks to provide real-time predictions of social behavior and operates primarily on the level of modeling individual agents. For instance, a network providing imagery or other persistent sensory data would rely on an algorithm to distinguish between suspicious and "normal" behavior. The algorithm would be comprised of at least two parts: a model of "normal" behavior and a set of decision rules regarding how to compare real-time surveillance data to the model. The model may be developed in several different ways, such as deduction from theories of counterintelligence or law enforcement or induction following an initial data collection phase.

A common criticism against a behavioral economics approach to modeling large societies is one of complexity. However, by constructing a constrained and first-principles-based behavioral model for any network of actors, high-fidelity computational algorithms designed for the analysis of highly flexible structures and fluid streams in engineering applications may be readily applied. One emerging system theoretic tool, known as *model predictive control*, may be of particular interest when combined with online model order reduction. This technique, originally developed for very-high-order computational modeling of turbine engines (Hovland, Gravdah, & Wilcox, 2007) and recently extended to biological regulatory network shaping (Hovorka et al., 2004), is best known for its flexibility to predict future values of variables of interest while maintaining realistic constraints such as societal norms, rules, and laws. By adopting a microeconomic model, transactions and movements of actors of interests can be modeled through subjective utility maximization, providing for a large-scale dynamic system for the persistent video segment of interest. This model may be prescribed within the framework of choice theory models common in the behavioral sciences.

Although such a model will be highly granular, computational complexity may be circumvented while maintaining the critical dynamics of interests. Specifically, by incorporating *dynamic* (online) reduced-order-modeling techniques, the algorithm can effectively “focus” on the essential movement of interest. In the case of persistent surveillance video, this could be the motion of a target vehicle or the financial transactions of a network of individuals. The computational method is performed in discrete time, which has the added benefit of smooth application to discrete frame-by-frame data delivery from persistent surveillance imagery. As a tool for homeland security, the method is capable of intelligently prescribing continuous inputs into the scene that would effectively *drive* an actor towards a desired state, such as an interception point.

Synthesis

Information gathered from persistent surveillance promises to revolutionize domestic situational awareness, providing instantaneous and synchronized knowledge of financial transactions, group behaviors, and individual actions of interest to the homeland security community. Identifying individual actors and their social networks within data delivered by persistent surveillance platforms is an important technical challenge with the potential to dramatically improve domestic intelligence. While many social modeling techniques exist, it is evident that a behavioral sciences model is most appropriate for modeling the interactions among agents of interest within surveillance data. Typically such models are quite complex. However, by leveraging existing and proven computational capabilities common to engineering applications and systems theory, high-fidelity modeling and identification of network dynamics from a large data set become mathematically tractable.

Future Directions

Given the major shift in national security focus from large, Cold War military rivals to smaller, autonomous terror cells in the 21st century, persistent surveillance information gathering and data processing techniques should be optimized for combating these new opponents. One of the highest impact methods for accomplishing this evolution in surveillance paradigms would be to develop a methodology for defining social networks using persistent surveillance to autonomously determine where known targets are going, which buildings they enter, and which vehicles they use. While the concept of using persistent surveillance to define relevant social networks has been tangentially referenced in defense media and topical research, there has been little focus on developing a system to implement the idea in applied engineering. Using real-time data to discover social networks would strongly benefit the U.S. Department of Homeland Security. Despite widespread skepticism regarding social scientists' ability to predict social behavior in real or near-real time, recent applications have demonstrated the maturity of software that draws on microeconomic behavioral models and statistics for this purpose (Flynn, Juergens, & Cantrell, 2008; Wyatt et al., 2008; Choudhury et al., 2006).

Based on our literature review, we conclude that traditional rational actor models with two modifications—considering actors' preferences for the trajectory of the entire social system and incorporating both active and inactive actors—holds great promise for achieving real- or near-real-time prediction of social behavior by drawing on persistent surveillance data. Validating the proposed framework on a computational model system would be followed by actual implementation on persistent surveillance imagery for empirical studies.

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References

Adams, A. (2008). *Multispectral persistent surveillance*. Unpublished doctoral dissertation, Rochester Institute of Technology.

Barnes, J. E. (November 2, 2009). Military refines a "constant stare against our enemy." *The Los Angeles Times*.

Boudreau, J. W. (2004, November). Organizational behavior, strategy, performance, and design in management science. *Management Science, 50*(11), 1463–1476.

Carley, K. (2002). Computational organization science: A new frontier. *Proceedings of the National Academy of Sciences of the United States of America, 99*(10), Supplement 3, 7257–7262.

Choudhury, T., Philipose, M., Wyatt, D., & Lester, J. (2006, March). Towards activity databases: Using sensors and statistical models to summarize people's lives. *IEEE Data Engineering Bulletin, 29*(1), 49–56.

Collins, R. T., Lipton, A. J., Fujiyoshi, H., & Kanade, T. (2001). Algorithms for cooperative multisensor surveillance. *Proceedings of the IEEE, 89*(10), 1456–1477.

De Marchi, S. (2005). *Computational and mathematical modeling in the social sciences* New York: Cambridge University Press.

Downs, A. (1957). *An economic theory of democracy.* New York: Harper.

Epstein, J. (2007). *Generative social science: Studies in agent-based computational modeling.* Princeton: Princeton University Press.

Epstein, J. (1997). *Nonlinear dynamics, mathematical biology, and social science.* Reading, MA: Addison-Wesley.

Flynn, M. T., Juergens, R., & Cantrell, T. L. (2008). Employing ISR: SOF best practices. *Joint Force Quarterly, 50*, 56–61.

Gell-Mann, M. (1995). What is complexity? *Complexity, 1*(1).

Gill, P., & Swartz, T. (2004). Bayesian analysis of directed graphs data with applications to social networks. *Journal of the Royal Statistical Society Series C (Applied Statistics), 53*(2), 249–260.

Goss, J. (1995, April). We know who you are and we know where you live: The instrumental rationality of geodemographic systems. *Economic Geography, 71*(2), 171–198.

Hall, P., & Taylor, R. (1996). Political science and the three new institutionalisms. *Political Studies*, *44*, 936-957.

Hanneman, R. A. (1998). *Computer-assisted theory building: Modeling dynamic social systems.* Newbury Park, CA: Sage.

Herman, R. (1992, March–April). Technology, human interaction, and complexity: Reflections on vehicular traffic science. *Operations Research, 40*(2), 199–212.

Holland, J. H. (1998). *Emergence: From chaos to order.* Reading, MA: Helix Books.

Holland, J. (1992). Complex adaptive systems. *Daedalus, 171*, 17–30.

Hovland, S., Gravdah, J. T., & Wilcox, K. (2007). Explicit model predictive control for large scale systems via model reduction. *AIAA Journal Guidance Control and Dynamics, 31*.

Hovorka, R., Canonico, V., Chassin, L. J., Haueter, U., Massi-Benedetti, M., & Federici, M. O. (2004). Nonlinear model predictive control of glucose concentration in subjects with type 1 diabetes. *IOP Physiological Measurement*, *25*, 905–920.

Huisman, M., & van Duijn, M. (2005). Software for social network analysis. In P. J. Carrington, J. Scott, & S. Wasserman (Eds.), *Models and methods in social network analysis.* Cambridge: Cambridge University Press.

Knoke, D., & Yang, S. (2008). *Social network analysis* (2nd ed.). Los Angeles: Sage.

Liebrand, W. B. G., Nowak, A., & Hegselmann, R. (Eds.) (1998). *Computer modeling of social processes.* London: Sage.

Liu, H., Salerno, J., & Young, M. J. (Eds.) (2009). *Social computing and behavioral modeling.* New York: Springer Science.

Liu, L., & Eck, J. (Eds.) (2008). *Artificial crime analysis systems: Using computer simulations and geographic information systems.* Hershey, NY: Information Science Reference.

Lustick, I. S., & Miodownik, D. (2009, January). Abstractions, ensembles, and virtualizations: Simplicity and complexity in agent-based modeling. *Comparative Politics, 41*(2), 223–244.

Lustick, I. S., Miodownik, D., & Eidelson, R. J. (2004). Secessionism in multicultural states: Does sharing power prevent or encourage it? *American Political Science Review, 98*(2), 209–230.

Mitchell, M. (1996). *An introduction to genetic algorithms.* Cambridge, MA: MIT Press.

Nuckols, J. R., Ward, M. H., & Jarup, L. (2004, June). Using geographic information systems for exposure assessment in environmental epidemiology studies. *Environmental Health Perspectives, 112*(9), 1007–1015.

Olson, M. (1965). *The logic of collective action.* Cambridge: Harvard University Press.

Reis, B. Y., Kirby, C., Hadden, L. E., Olson, K., McMurry, A. J., Daniel, J. B , & Mandl, K. D. (2007). AEGIS: A robust and scalable real-time public health surveillance system. *Journal of the American Medical Informatics Association, 14*(5), 581–588.

Sarnoff Corporation. (2009). Sarnoff to demonstrate persistent surveillance and biometric products at AIS 2009 conference. Retrieved May 26, 2009, from http://www.sarnoff.com/press-room/news/2009/09/21/asis-2009

Shepsle, K. (1989). Institutional equilibrium and equilibrium institutions. *Journal of Theoretical Politics, 1*(2), 131–47.

Waldrop, M. (1992). Complexity: The emerging science at the edge of order and chaos. New York: Touchstone.

Wang, F.-Y., Carley, K. M., Zeng, D., & Mao, W. (2007, March/April). Social computing: From social informatics to social intelligence. *IEEE Intelligent Systems, 22*(2), 79–83.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications.* New York: Cambridge University Press.

Wasserman, S., & Pattison, P. (1996). Logit models and logistic regressions for social networks: An introduction to Markov graphs and *p*. *Psychometrika, 61*(3), 401–425.

Wyatt, D., Choudhury, T., Bilmes, J., & Kitts, J. (2008, September). Towards the automated social analysis of situated speech data. *Proceedings of UbiComp '08*, Seoul, Korea.

Yao, Y., Chen. C. H., Abidi, B., Page, D., Koschan, A., & Abidi, M. (2010). Can you see me now? Sensor positioning for automated and persistent surveillance. *IEEE Trans Syst Man Cybern B Cybern, 40*(1), 101–115.