Modeling Civil Violence: An Evolutionary Multi-Agent, Game Theoretic Approach

C. K. Goh, H. Y. Quek, K. C. Tan and H. A. Abbass

Abstract—This paper focuses on the design and development of a spatial Evolutionary Multi-Agent Social Network (EMAS) to investigate the underlying emergent macroscopic behavioral dynamics of civil violence, as a result of the microscopic local movement and game-theoretic interactions between multiple goal-oriented agents. Agents are modeled from multi-disciplinary perspectives and their behavioral strategies are evolved over time via collective co-evolution and independent learning. Experimental results reveal the onset of fascinating global emergent phenomenon as well as interesting patterns of group movement and behavioral development. Analysis of the results provides new insights into the intricate behavioral dynamics that arises in civil upheavals. Collectively, EMAS serves as a vehicle to facilitate the behavioral development of autonomous agents as well as a platform to verify the effectiveness of various violence management policies which is paramount to the mitigation of casualties.

I. Introduction

Civil violence is a term widely used in the context of modern society to describe associated acts of violation and destruction, carried out as a sign of defiance against a central authority or between opposing groups of people. Civil violence manifests itself in many forms and is often categorized depending on its nature as well as degree of involvement and severity, ranging from small-scale riots to large scale revolutions such as civil and ethnic wars.

The traditional approach of viewing civil violence as the consequence of pent-up grievances by society has varied widely in the modern context. Collier and Hoeffler [1] look at the possible economic causes behind it while Regan and Norton [2] consider it as a function of mass mobilization. Substantive differences are also identified between ethnic and non-ethnic motivated violence [3], [4]. It was quoted that "each war is as different as the society producing it" [5] and causes should be analyzed with regards to the nature of the conflict itself. Considerable efforts have been expended to study the underlying structure of social conflicts with regards to the widespread collective, random movement of crowds and behavioral interactions between people [6].

Empirical models of social conflicts have been simulated in the form of riot games [7] via game theoretic models [8], [9] and social networks, offering statistical, spatio-temporal analysis [10] of conflict and its role playing dynamics [11] in crowds. These models generate emergent collective social phenomenon materialized through behavior clustering [12], mass-mobilization [13] and massive conflicts [14], which are indisputably a direct reflection of the outcome of civil violence in the context of real-life scenarios. This provides the necessary avenue to investigate strategies for managing civil violence [15]. It is noted that the behavioral evolution of multiple conflicting agents at the microscopic level is consistent to the real world scenario, given that humans learn and adapt. Nonetheless, the notion of evolving learning agents in the context of a civil violence model has received little attention from the research community.

This paper focuses on the design and development of a spatial Evolutionary Multi-Agent Social Network (EMAS) model for examining the emergent macroscopic-behavioral dynamics of civil violence, as a result of microscopic local movement and game-theoretic interactions between multiple goal-oriented agents in various scenarios. Agents are modeled from multi-disciplinary perspectives and their tactics are evolved over time via collective co-evolution and independent learning. Experimental results reveal the onset of fascinating global emergent phenomena and interesting patterns of agent movement and behavioral development. Analysis of the results demonstrates how the collection of microscopic attributes interconnects with the macroscopic characteristics of civil violence and provides new insights into the rich dynamics that arises from civil upheavals. Collectively, EMAS serves as a vehicle to facilitate the autonomous behavioral development in agents as well as a platform to verify the effectiveness of various violence management policies which is paramount to the mitigation of casualties. Organization of the paper is as follows: section II presents a short review of existing work and the general framework of EMAS. Section III introduces the model specifications. Section IV discusses the evolutionary and learning mechanisms that drive the autonomous behavioral changes in agents. Section V collates and evaluates the series of simulation results based on different situational setups and model extensions. Section VI concludes the paper with a broad summary of discussion as well as some comments on areas where future work can be embarked on.

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II. Evolutionary Multi-Agent Social Network

A. Overview

Numerous empirical-based computer simulations have been constructed over the years to model complex dynamic systems [16], [17], [18] in numerous areas of disciplines.

The procedure involves breaking down complex verbal theories and translating them into semi-mathematical equations which are integrated systematically into model design. Developed models are simulated over time to create meaningful trends and patterns for analyzing and drawing conclusions. The same approach has been taken by Epstein [11] to model the state of civil violence involved in a decentralized rebellion against a central authority as well as communal violence between two warring ethnic groups. By virtue of its simplicity, the elegant agent-based approach is able to bring forth salient features of violence dynamics through simple empirical rules and equations governing the microscopic interaction between agents. Subsequently, the MANA model [15] provided an extension to Epstein's model by introducing specific movement strategies which are aimed at correcting the purely random movement of agents. Situngkir [14] also used empirical formulation to model the phenomenon of massive conflict by invoking its analogy with the macro-micro link in Sociological Theory.

B. General Framework of EMAS

Inspired by the previous models, the proposed EMAS framework consists of a civil violence model (CVM) and an evolutionary engine (EE) as shown in Fig.1. Interaction between agents is formulated in a game-theoretic manner via the CVM while collective co-evolution of agent strategies is performed in the EE, via an evolutionary algorithm (EA). Individual learning is undertaken as agents move and interact with one another. This broadens the horizon of discussion and adds realism to the resulting model.
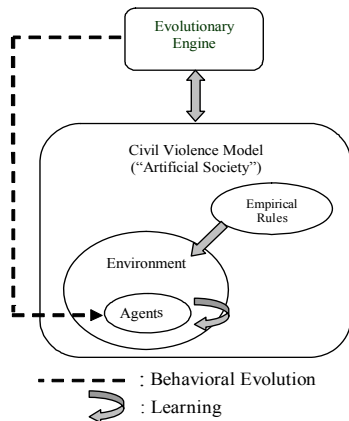

Fig. 1. Framework of the Evolutionary Multi-Agent Social Network

C. Game Theoretic Interaction

The CVM models agent interaction in a game-theoretic manner, based largely on the general features of a spatial Iterated Prisoner's Dilemma (IPD) game [19]. At any one instance, each agent will establish game play with every other opposing agent within the vision radius in a pair-wise manner. Interaction is subjected to the spatial constraint of a 2D-Grid in the CVM and only opposing agents within the vision radius are allowed to interact. No interaction will occur between agents of the same type and isolated agents. Quiescent civilians do not play the game even though they exist in the multi-agent system. In view of the difference in

numbers between opposing agents, the model uses three separate payoff matrices corresponding to the situations where the number of agents may be equal to, more than or less than the number of opposing agents. The matrices are constructed with the aim of each agent group to maximize its own benefit and minimize casualties. Consider the case when cops outnumber actives in a spatial area of interaction.

a. If both groups D, cops gain the upper-hand due to the sheer superiority in numbers. With their successful intervention to stem riots, cops are awarded the temptation payoff (T). Actives receive the sucker payoff (S) due to their inability to create havoc and the large casualties sustained.

b. If both groups C, payoff reverses in favor of actives. Cops, while protecting the general population, have missed a good chance to arrest the minority actives. The act of C paid off for the actives as they successfully avoided conflict with the massive cop population, justifying the award of T.

c. When cops C and actives D, both get the punishment payoff (P) as C and D are executed under the inappropriate situations. Cops should have D to confront the actives while actives should have C to avoid declaring an open challenge to the domineering law enforcers and inviting casualties.

d. When cops D and actives C, a sound Nash equilibrium is attained - where the majority group exerts its domineering presence and the minority group avoids direct conflict so as to minimize casualties. Given the in-balance in strength, this accounts for the situation where benefits of both groups are considered. This justifies reward payoff (R) for both groups.

Agent Type 2			
		COOPERATE	DEFECT
Agent Type 1	COOPERATE	3,3 (R)	0,5 (S)
	DEFECT	5,0 (T)	1,1 (P)

(a)

Agent Type 2			
		COOPERATE	DEFECT
Agent Type 1	COOPERATE	1,4 (S)	2,2 (P)
	DEFECT	3,3 (R)	4,1 (T)

(b)

Agent Type 2			
		COOPERATE	DEFECT
Agent Type 1	COOPERATE	4,1 (T)	3,3 (R)
	DEFECT	2,2 (P)	1,4 (S)

(c)

Fig. 2. Payoff matrix (Type1, Type 2) when the number of Type 1 agents is (a) equal, (b) greater or (c) lesser than the number of Type 2 agents.

III. CIVIL VIOLENCE MODEL

The CVM consists of multiple groups of agent interacting and coexisting in an artificial society. It comprises of three distinct components: The agents, environment and empirical rules governing the interaction between agents.

A. Agents

Three different types of agents are specified in the CVM - cops, quiescent civilians and actives. In accordance to Berdal and Malone [20], grievance and greed [21] are modeled as the two idealized components that collectively measure the tendency of quiescent civilians to join actives in their revolt against a central authority. Grievance (G) is defined as a function of the overall Hardship ($H_{overall}$)

experienced by an agent and the Legitimacy (*L*) of a centralized authority. Mathematically, *G* is given by

$$G = H_{overall} \cdot (1-L) \qquad (1)$$

Greed (*Gr*) is defined collectively as the perceived opportunity to gain wealth where $Gr = U(0,1)$. According to Collier and Hoeffler [21], grievance triggers off a revolt while greed sustains the state of civil upheaval. Therefore, the tendency to revolt (*Rev*) is formulated as

$$\text{Re}\,v = T_f \cdot G + (1-T_f) \cdot Gr \qquad (2)$$

where $T_f = [0,1]$ is the time factor correlating *G* and *Gr* and is inversely related to the active duration, T_{ad} of an agent. The above formulation ensures that *Gr* becomes the dominant component over *G* as the act of civil violence is prolonged. The net risk *N*, perceived by an agent with an intention to revolt is modeled by

$$N = R_A \cdot P_a \cdot J_{max}{}^{J_\alpha} \qquad (3)$$

where R_A is the agent's inclination to take risk, P_a is the probability of getting caught and J_{max} is the maximum jail penalty with J_α as a factor to determine the corresponding deterrent effect. The decision to revolt will depend on the net active index (*NAI*) of each agent where

$$NAI = \text{Re}\,v - N \qquad (4)$$

B. Empirical Rules

Empirical rules govern interaction of agents and ensure proper functioning of the CVM. They are crucial for the formation of desired simulation outcomes that depicts and possibly recreates real-life scenarios that are vividly portrayed in the literature on revolutions and civil violence.

B.1 State Transition Rule

Agents become active if $NAI > A_{threshold}$. Transitions only occur between actives and quiescent civilians but not cops.

B.2 Jail Release Rule

Jailed agents will either be converted back to quiescent state or revert back to active state with a certain probability after release (Fig. 3). This effectively takes into account the effect of rehabilitation – high chances of converting jailed agents back to law-abiding citizens and also the curse of the minority – low possibility that persistent rebels will continue in their old ways upon release from jail.
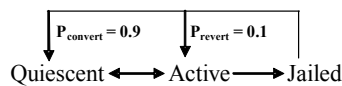
Fig. 3. State transition flow diagram between different agent states

B.3 Movement Rule

Movement of agents in the coordinate grid space between consecutive time-episodes is modeled based on a 2-D Cellular Automata (CA) Model [22], [23]. The rules for updating cells are modified from John Conway's Game of Life. In the proposed model, position of each agent at the next time episode is determined by the current position of that agent and also the current states of all neighboring cells within the agent's local vision radius, as modeled by a Moore's 8-directional CA neighborhood. In general, the isolation and overcrowding rules govern movement on the 2D grid in the next time episode. Since isolated agents are likely targets of attack by the opposing group, agents will move to a safer position if the number of similar agents in the neighborhood is low. Likewise, with the danger of losing sight of the situation in overcrowded situations, densely packed agents will also tend to move towards sparsely filled regions. On top of the generalized rules of agent movement, each distinct agent type also has its own set of preference strategies. Some realistic movement strategies corresponding to each of the three agent types are mentioned in Table I.

TABLE I
MOVEMENT STRATEGIES FOR DIFFERENT AGENT TYPES

Movement strategies	Agent Type	Description
Avoid the Cops	Actives	Actives attempt to minimize contact with cops in order to lower chances of arrest.
Stay if favorable	Actives	Actives prefer to stay put rather then venturing out into the unknown if current location is safe.
Kill the Civilians	Actives	Actives take initiative to root out and kill any unarmed civilians in sight.
Pursue Actives	Cops	Cops take initiative to arrest actives.
Protect Civilians	Cops	Cops take initiative to protect the general population from the threats of actives.
Run from Actives	Quiescent	Quiescent civilians run for their lives when actives are on a killing spree.

B.4 Arrest Rule

A successful arrest is made when a cop wins an iterated IPD game set against an active within the neighborhood of interaction. Arrested agents will vacate the cell occupied and is put out of action for a number of time episodes is given by

$$J = \begin{cases} 1 + J_{max} \cdot \dfrac{J_H}{J_{H\,max}} & \text{if } J_H \leq J_{H\,max} \\ \\ I_{max} & \text{otherwise} \end{cases} \qquad (5)$$

where J_H refers to the number of times an agent have been arrested, $J_{H\,max}$ denotes the maximum number of times tolerable for the repetition of crime in society's view. I_{max} is either a sentence for life imprisonment or a fixed jail term. Taking into account group effects, cops have higher chances of apprehending actives if they are pursuing the same one.

C. Environment

The environment defines an *N x M* 2-D coordinate grid where different agents move about and interact in. In the 2D landscape, cops are depicted by circles with black stars; actives by shaded circles and quiescent civilians are denoted

by un-shaded ones. Together with various global and situational parameters, the environment allows access to the global state of civil unrest at any one time episode and provides information about the spatial interactions between agents on both the global and local scales.

IV. EVOLUTIONARY ENGINE

Agents improve their strategies by collective co-evolution and independent learning. The two processes allow agents to shape their own behaviors over time and react appropriately to unforeseen circumstances. Behavior development of agent is by means of co-evolution where different groups of agents are evolved by the EE independently. This framework has been widely used to understand population dynamics and study the extent of cooperation in Evolutionary Game Theoretic (EGT) Models [24]. In the proposed model, the co-evolutionary phase is conceptualized in analogy to the exchange of ideas and strategies in the real life context, between members of the same agent group (Fig. 4).
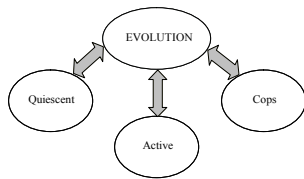
Fig. 4. Co-evolution of different agent groups

Through the multi-directional flow of information, agents with weaker strategies learn from stronger ones by adopting some of the better traits. Overall fitness of each population is increased as strategies become increasingly more competent with each elapsed generation. Chromosomal representation of each agent is a 14-bit binary string which encodes the tactics used. Each set of 4 bits which records the previous moves of made by both agent and opponent will be decoded to either C or D and used according to the nature of the situation (Fig. 5). The collection of all agent strategies is evolved according to an algorithmic workflow in Fig. 6.
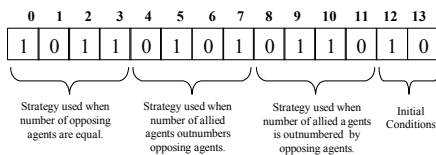
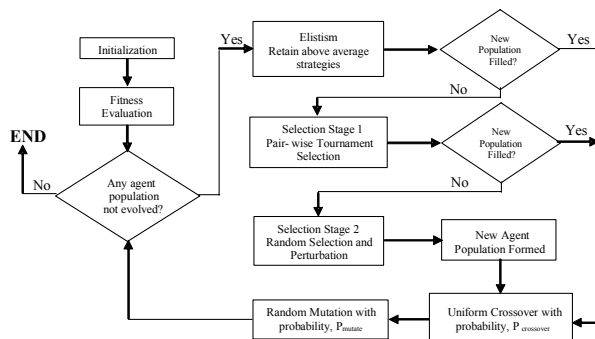Fig. 5. Binary encoded genotype for agent strategy

Fig. 6. Workflow for evolution of agent strategies

Learning is carried out independently by agents to improve their performance based on some form of heuristics that utilize domain-specific information available at hand or from previous experiences. Using the Lamarckian learning scheme, all of which has been acquired by, laid down, or changed in the organization of individuals during the course of their life is conserved and transmitted to new individuals which proceed from those which have undergone those changes [25]. Generation of new agents is guided by lessons learned from past generations, rather than a form of trial and error process [26]. The basis of learning is formulated by recording the number of wins and loses accumulated by a particular agent strategy in the course of game play. Overall, the interplay of evolution and learning makes the CVM a close replica of a real world situation and creates interesting behavioral dynamics over time as agents move and interact across the spatial 2D landscape.

V. SIMULATION RESULTS

Simulations are carried out in the Microsoft Visual C++ environment. Model extensions of varying complexity are introduced to track interesting behavioral development of each agent population. Spatial and temporal responses of the CVM are investigated via a series of test settings.

A. Basic CVM Response

Interesting findings have been unrevealed in the course of the simulation runs. Temporal response of the basic CVM showed the presence of "Punctuated Equilibrium" [11] - long periods of relative stability punctuated by outburst of rebellious activities. This affirms that peace and stability is essentially a state of dynamic equilibrium that emerges from the collective interactions between agents rather than a state of static equilibrium itself (Fig. 7).
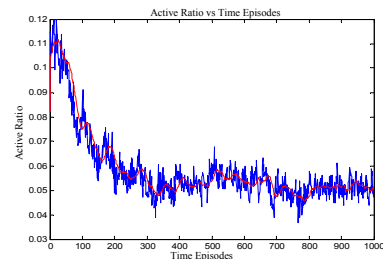
Fig. 7. "Punctuated Equilibrium" in temporal response

The spatial interaction between agents shows a tendency for patterns of group clustering to occur amidst the random agent movement across the 2D space. Le Bon proposes in his theory that "crowds seem to be governed by a collective mind, and that contagion causes members to experience similar thoughts and emotions" [27]. Famous psychologist, Sigmund Freud [28] further reinforces the fact that "individuals, by joining crowds, are able to satisfy some basic needs for membership, hostility, and so on." This behavioral and psychological need of agents often accounts for the conglomeration of scattered actives into small clusters as well as the amalgamation of smaller clusters into larger ones as seen in Fig. 8(a)-(b).
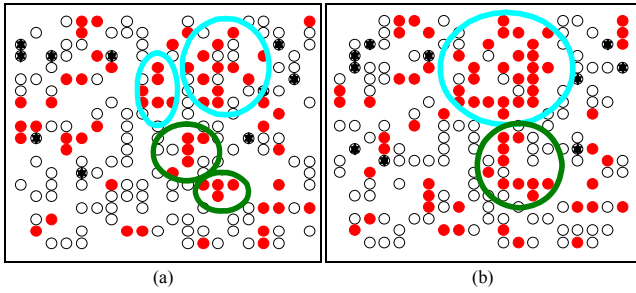
Fig. 8. Spatial response depicting formation of group clusters

A common challenge posed to the police force in crowd management is to disperse clusters of rebels before they turn into massively large mobs, which will then be beyond the realm of control. An intuitively effective cop strategy is thus one that space cops in strategic positions that will prevent the formation of huge clusters. Spatial response that depicts the display of such tactics is shown in Fig. 9(a)-(d).
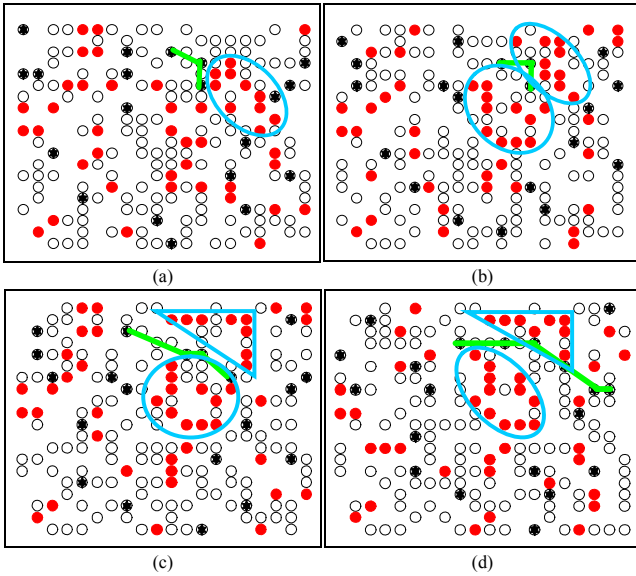

Fig. 9. Spatial response depicting crowd dispersing tactics by cops

Another salient feature of human behavior is also observed - the ability to deceive and put on a false front if situations with dangerous encounters are imminent. As illustrated in Fig. 10(a)-(b), two aggrieved agents appear as quiescent civilians in the presence of cops but quickly turned active when the cops adjacent to them move away.
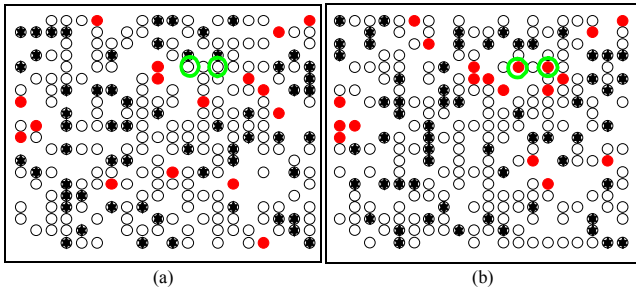

Fig. 10. Spatial response depicting acts of deception

It was quoted by famous military strategist, Sun Tzu that "Warfare is the art of deceit" [29]. An element of surprise which precedes any attack (e.g. guerilla warfare) is one of the pertinent factors that led to the success of numerous revolutions and uprisings. By practicing the art of deception, actives are able to control and conceal their emotions by appearing to be quiescent civilians. By doing so, they avoid detection and arrest while waiting patiently for the right opportunity to strike. This has far-stretching repercussions as it lengthens the duration for the actual civil unrest and is one of the contributing factors that make the task of apprehending active remnants increasingly difficult

B. Different cop sizes

By varying the cop size, the inverse relationship between active ratio and cop numbers is also established in Fig. 11. As increasing number of cops are injected into the CVM, the decline in the peak and settling active ratio gets less and less significant. This indicates the presence of a saturation state. Further decrease in the active ratio will have to come from other aspects of improvement e.g. longer jail term.
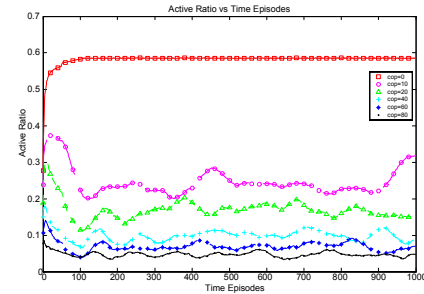

Fig. 11. Family of temporal response curves for different cop sizes

Interestingly, the shapes of the actual and perceived active ratio curves tend to be similar (Fig. 12) with a consistent gap between them. It can be deduced that deceptive behavior is largely exhibited by a small and unswerving group of active and this phenomenon is always present despite the cop size.
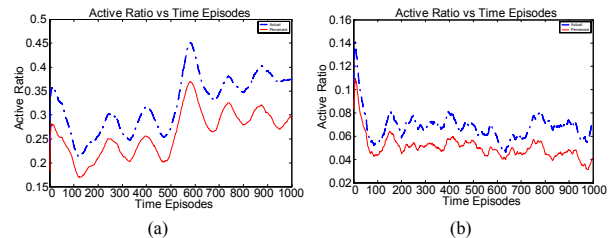

Fig. 12. Actual and perceived active ratio for (a) low, (b) high cop size

Strong correlation between the population composition and the cooperation level also exists (Fig. 13). With low cop density, the cop-to-active ratio in specific local spatial neighborhoods is low, making the ambience of rebellion superseding for actives to defect. With higher cop density, actives undergo greater contemplation before deciding to show their discontent publicly. The higher cooperation ratio undergoes larger fluctuation due to the tendency to cooperate in areas of high cop density and defect whenever an occasional opportunity to revolt comes along. Grievance is found to be relatively stable as the cop size increases from Fig. 14(a)-(b). It is generally high for actives across the active community, with persistent activists having above average greed levels.
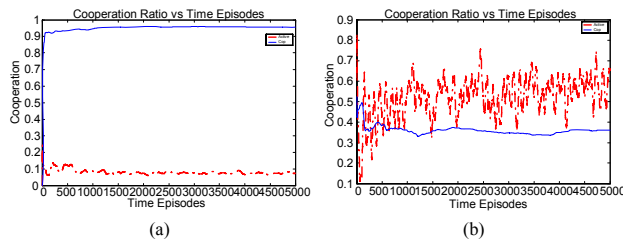
Fig. 13. Cooperation profile for (a) low and (b) high spatial cop density
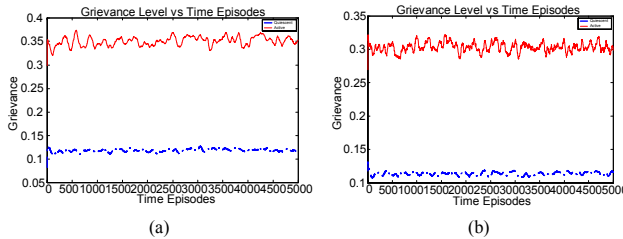

Fig. 14. Grievance profile for (a) low and (b) high spatial cop density

Increasing the cop size effectively removes these activists, leaving a mildly aggrieved active population that exhibits lower average population greed. This is indicated by a drop in the average population Greed level in Fig. 15(a)-(b). The results show that Grievance is the primary factor and more stable component that sparks off the onset of civil unrest.
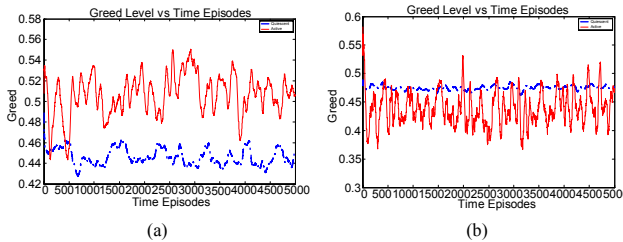

Fig. 15. Greed profile for (a) low and (b) high spatial cop density

The average active history measures the tendency of behavioral switching occurring throughout the civilian population. As the cop size increases from Fig. 16(a)-(b), it is lucidly identified that there is a general trend of increasing active history for the active community as depicted by the increasing divergence in active history between the active and quiescent populations. Since switching occurs when an agent changes from the quiescent to the active state, the bulk contribution to the increase in active history comes from the continual reversion of agents back to the active state after their release. This is an indicator that the active population is made up largely of persistent rebels who refuse to learn from their old ways despite the long period of rehabilitation.
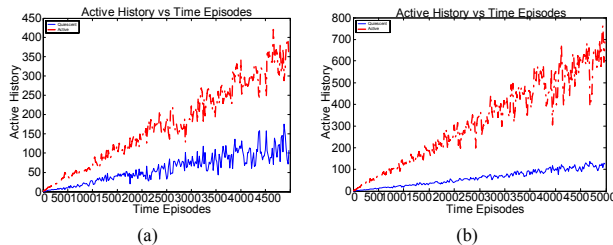

Fig. 16. Average active history for (a) low and (b) high spatial cop density

The active duration keeps track of how long each active

has been rioting. With a small cop size (Fig. 17(a)), the variance in active duration across the civilian population is large, with a higher concentration of actives rioting for large time episodes without being arrested. With an increase in number of cops (Fig. 17(b)), the trend reverses as depicted by a lower variance in active duration and subsequently larger concentration of actives in the lower active duration bins of the histogram. A greater cop size generally entails a lower level of rebel activities from time to time.
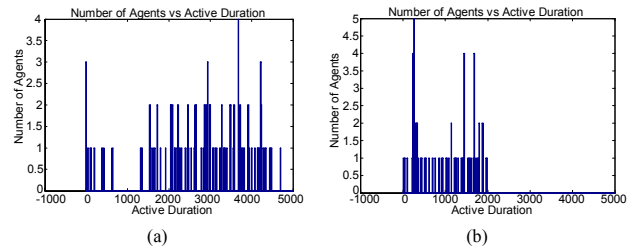

Fig. 17. Active duration distribution for (a) low, (b) high spatial cop density

C. Influence by Defectors and Charismatic Leaders

The basic game theoretic CVM is extended to account for the subtle influence exerted by actives on the neighboring quiescent civilians. Defectors are capable of exerting substantial influence on the existing population through demonstration of bold acts of rebelliousness. Charismatic leaders influence the crowds in more subtle ways and tend to exercise more caution, showing their true nature only in favorable situations. From investigation, it is found that influence generally causes an initial upsurge of actives as more mildly aggrieved agents are incited to revolt. Addition of defectors allows gradual built up of tensions across the entire population over time, which in turn manifests itself as unprecedented occurrence of outbursts. Presence of leaders on the other hand causes a larger proportion of the civilian population to be active at any one time. Both sources of influence promote the onset of deceptive behavior to some degree towards the later stages of the civil upheaval. It is also found that introducing defectors and leaders at the early stages entails greater strike dynamics and behavioral developments compared to introducing them later.

D. Variation of jail terms

Increasing the fixed jail terms generally acts as a source of deterrence which causes a decrease in the overall active ratio, dampening the scale of fluctuation and frequency of outbursts (Fig 18). This, however, is effective only over a short time span. The system of variable jail terms - where mistakes of initial offenders are tolerated while repeated offenders are punished heavily constitute a fairer system of justice which is also more efficient in controlling the scale of civil unrest on a long term basis. The increasing jail term imposed for each successive attempt to revolt serve as a profound factor to deter agents from joining the rebellion.

In addition, deceptive behavior is also increased in the active community when the jail sentence is increased in the small to medium range. This is illustrated by the increase in cooperation ratio from Fig. 19(a)-(b). This is because agents with an intention to revolt eventually learn of the high

opportunity costs that are incurred to them in the event that they are arrested over a number of times. Nevertheless, since deceptive behavior in the active community is cultivated through information exchange between fellow actives and constant interaction with cops, large and excessive jail terms tend to minimize the chances of cop to active interaction as well as the possibility of knowledge exchange for arrested actives. This impedes autonomous behavioral development and lowers the degree of deceptive behavior among actives, triggering the onset of defect-oriented behavior instead (Fig. 19(c)-(d)). It is thus intuitive that one way of curbing civil unrest and lowering the active remnants is to minimize contact between actives by lengthening the jail sentences of arrested agents, thus isolating them from the community.
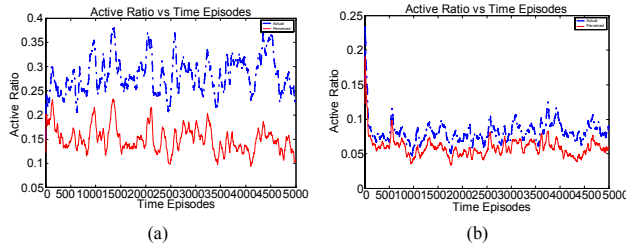

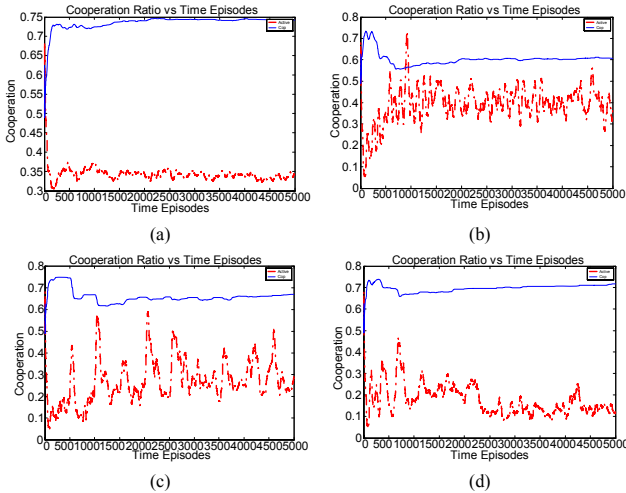Fig. 18. Active ratio for (a) small and (b) large jail terms

Fig. 19. Cooperation profile for (a) small, (b) medium, (c) large and (d) excessive jail terms

Similar to the increase in cop size, increasing the jail terms also lowers the average population greed and increase the extent of behavioral switching within the entire civilian population. Persistent actives are found to be largely greedy in nature. This reinforces and validates the nature of greed as a factor for fueling the continual willingness of rebels to carry out acts of civil violence. Nonetheless, the dynamic range of the active duration is less affected by the length of jail terms as opposed to the case with increasing cop size.

E. Casualty Model

Finally, to collate everything together, a simple casualty model that consists of peacekeepers, perpetuators and quiescent civilians is constructed to simulate a close world resemblance of a civil unrest situation and at the same time assess the effectiveness of different violence control policies

with respect to the mitigation of casualties. In the setup, perpetuators constitute 10% of the total civilian population size and are capable of eradicating quiescent civilians. From Fig. 20(a)-(d), rapid annihilation of the quiescent population is observed when no intervening peacekeeping force is present to control and manage the state of civil unrest. The escalating increase in active ratio and sharp plunge in the number of quiescent civilians reflect the fact that a minority of perpetrators are capable of performing total extermination of a much larger unarmed population within a seemingly short time span. An apparent act of cornering is also exhibited by perpetrators in their attempt to wipe out the quiescent civilian population as shown in Fig. 20(c). An increasing jail penalty affects the long term profile of the civil unrest and helps to keep perpetrators in captive for longer periods of time. This strategy minimizes both the frequency and scale of killings as shown in Fig. 21(a)-(b).
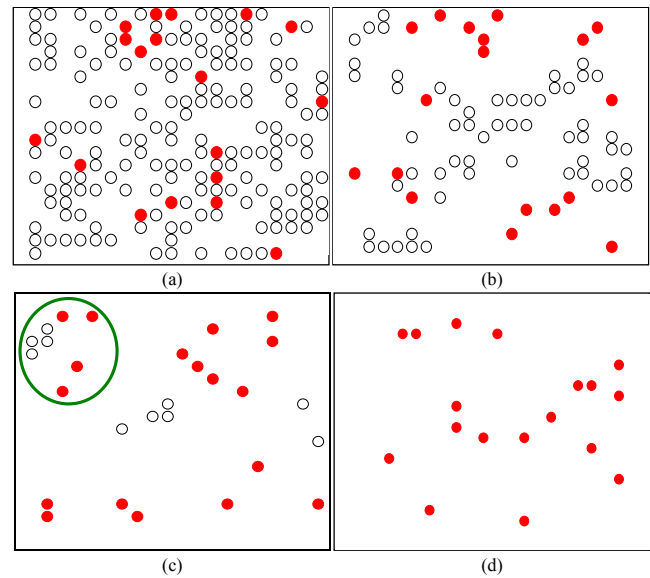

Fig. 20. Spatial response illustrating rapid annihilation of the quiescent population in the absence of any peacekeeping force
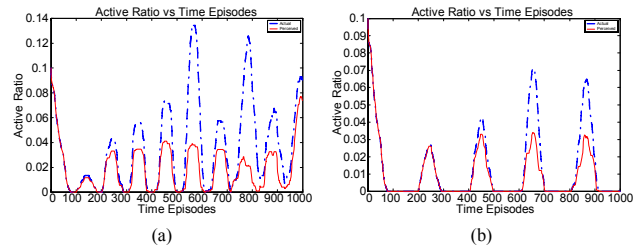

Fig. 21. Active ratio for (a) small and (b) large jail terms

Conversely, increasing the number of peacekeepers affects the short term profile, ensuring that perpetrators are arrested in the shortest possible time, at any point when they are let loose. The effect is seen by a more drastic drop in the initial quiescent population for a small peacekeeping force (Fig. 22(a)) compared to a small decrease with more peacekeepers (Fig. 22(b)). Nevertheless, an excessive peacekeeping force leads to overcrowding and worsens the prevailing state of civil upheaval as shown by the sharp decline in the quiescent population around the 200th time episode (Fig. 22(b)). It can be inferred that a large

peacekeeping force is needed initially to control and manage the presence of perpetrators, so that killings can be minimized. Once the situation of civil unrest stabilized, an excessively large peacekeeping force actually proved to be a drawback more than an advantage. Overall, though increasing jail term proves to be more efficient in the preservation of survivors, a balance of both factors e.g. an appropriate size of peacekeepers and a substantial jail term, is essential for achieving the lowest possible casualty rate.
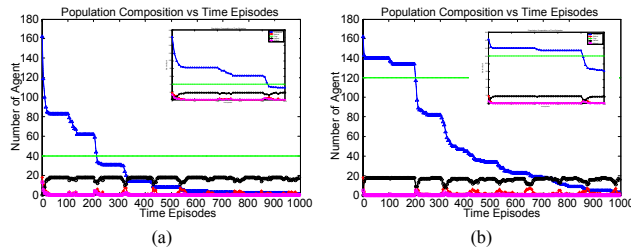

Fig. 22. Population dynamics for (a) small, (b) large peacekeeping force

VI. CONCLUSION

In conclusion, it can be gathered from the paper that the EMAS model replicates interesting macroscopic temporal statistics and spatial patterns of movement through the microscopic interaction and behavioral development of agents, which occurs as their strategies evolve autonomously under information exchange and independent learning. Studying how the underlying behavioral dynamics evolve under different situational setups is crucial to the holistic understanding of the fundamental nature of civil violence.

Future work can be embarked to improve the existing multi-agent social network model by studying the evolution of specific movement strategies over time, impact of vision radius and situational awareness on the performance of agents, adopting an N-player IPD model of game theoretic interaction with larger memory capacity and to explore into other interesting areas of behavioral development as stated in numerous literatures on social sciences. Maturity of such multi-agent models will not only serve as a platform to verify complex social theories but more importantly as an avenue to simulate real life scenarios of civil violence (e.g. rebellion, genocide etc) in the hope to devise appropriate violence management measures that is paramount to the mitigation of casualties in such unforeseen events.

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