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Realistic decision-making processes in a vaccination game

Yoshiro Iwamura *, Jun Tanimoto

Interdisciplinary Graduate School of Engineering Sciences, Kyushu University, Kasuga-koen, Kasuga-shi, Fukuoka 816-8580, Japan

HIGHLIGHTS

- We establish new strategy adaptation model for vaccination games.
- The models presume that an agent decision-makes according to what extent free-riding can be successful.
- The models show different characteristic from the conventional rule based on Pairwise Fermi update.

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ABSTRACT

Previous studies of vaccination games have nearly always assumed a pairwise comparison between a focal and neighboring player for the strategy updating rule, which comes from numerous compiled studies on spatial versions of 2-player and 2-strategy (2×2) games such as the spatial prisoner's dilemma (SPD). We propose, in this study, new update rules because the human decision-making process of whether to commit to a vaccination is obviously influenced by a "sense of crisis" or "fear" urging him/her toward vaccination, otherwise they will likely be infected. The rule assumes that an agent evaluates whether getting a vaccination or trying to free ride should be attempted based on observations of whether neighboring non-vaccinators were able to successfully free ride during the previous time-step. Compared to the conventional updating rule (standard pairwise comparison assuming a Fermi function), the new rules generally realize higher vaccination coverage and smaller final epidemic sizes. One rule in particular shows very good performance with significantly smaller epidemic sizes despite comparable levels of vaccination coverage. This is because the specific update rule helps vaccinators spread widely in the domain, which effectively hampers the spread of epidemics.

1. Introduction

In recent years, pandemic worldwide infectious diseases have been considered to be one of the most serious and pressing environmental problems, particularly in urban areas where high densities of people are connected by high-speed and mass transportation systems. Including the Spanish flu (1918), the Asian flu (1957), the Hong Kong flu (1968), and the swine flu (2009), our historical perspective suggests that the flu may currently be the most serious threat to our safety.

To prevent infectious disease epidemics such as the flu, pre-emptive vaccinations may be effective [1]. Nevertheless, once herd immunity is established via high vaccination coverage, individuals are less motivated to commit to voluntary vaccination because herd immunity enables them to free ride and successfully avoiding infection while paying no cost of vaccination [1,2]. Therefore, the herd immunity inevitably becomes disrupted. This is the so-called "vaccination dilemma." The herd immunity works as a public good in the context of social dilemma games, such as the Chicken-type dilemma [3,4].

* Corresponding author.
E-mail address: 2ES16327S@s.kyushu-u.ac.jp (Y. Iwamura).

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Table 1
Payoff.

Strategy＼State	Healthy	Infected
Vaccination	$-C_r$	
Non-vaccination	0	−1

For the past decade, so-called vaccination games, which give a mathematical framework to account not only for epidemiologic dynamics but also for the voluntary vaccination behavior of individuals who face epidemics [5–12], have been studied. Of these, Fu et al. [6] built a pioneer model where agents, spatially distributed on an underlying network and exposed to infectious risk, learn their strategy of whether to commit to a vaccination from one of their neighbors. This idea exactly reflects the assumption of the vast majority of studies dealing with spatial prisoner's dilemma (SPD) games; this is called pairwise comparison based on a Fermi function (as described by PW-Fermi) [3]. Even though this is acceptable from the standpoint of evolutionary game theory, real human behavior toward vaccination seems to be more complex and diverse. It is because, in addition to copying one's neighbors, alterations in social behavior may be influenced by public information, such as that provided by the media. Fukuda et al. [7] took into account public information shared with all agents in the conventional framework formulated by PW-Fermi. In practice, their model assumes that an agent refers to the average social payoff of the strategy that a focal agent randomly selects from his/her neighbors. If the selected neighbor happens to be a non-vaccinator (meaning a defector in the usual SPD context), he/she compares his/her own payoff with the average defector's payoff via PW-Fermi and determines whether to commit to a vaccination. If the selected neighbor happens to be a vaccinator, the focal player makes a decision by comparing his/her own payoff with the cost of vaccination, which is always equivalent to the average payoff of a vaccinator.

As a different scenario, Xiao et al. [8] and Fukuda et al. [9] explored what happens if there are a number of "stubborn" agents, fixed as either vaccinators or non-vaccinators, implying agents who do not update their strategy. This idea was inspired by the zealot model of Masuda [13] and Matsuzawa et al. [14], which is likely to be observed in the real world.

Another important aspect of social efficiency is that the spatial distribution of vaccinators in a network significantly affects the final epidemic size, as several studies have indicated [8,9]. Therefore, how an assumed strategy updating rule influences the vaccinators' spatial distribution should be carefully explored.

Meanwhile, common sense and our usual observations in daily life suggest that someone's stochastic behavior of whether to commit to a vaccination is influenced by information of whether surrounding non-vaccinators successfully avoided infection in the previous time-step, because normal people tend to behave in a rational way to maximize his/her personal payoff by avoiding paying a vaccination cost if possible. In this study, we propose a new framework to emulate such people's behavior formulated via an agent's strategy adaptation rule.

This paper consists of the following. Section 2 describes the model setting of our new updating rule with respect to the conventional PW-Fermi rule. Section 3 presents and discusses the simulation results. Section 4 offers our concluding remarks.

2. Model setting

2.1. Spatial vaccination game

We consider a population of N agents in which every member adaptively undertakes vaccination behavior in the midst of a seasonal and periodic flu-like disease. We follow Fu et al. [6] and Fukuda et al., which deal with twofold dynamics: decision-making dynamics and SIR dynamics [15]. N agents are assigned to an underlying network. We assume a 2D square lattice with periodic boundaries of degree 4.

In the first stage, which indicates a vaccination campaign, agents decide their strategy, whether they vaccinate before an epidemic season, which is the second stage, explained latter. An agent who decides to vaccinate must pay a vaccination cost, C_v. For simplicity, we assume that a vaccinator gets perfect immunity for a single season. Conversely, a non-vaccinator is exposed to the risk of infection during the epidemic season. In the very first vaccination campaign, which is the initial situation of a simulation episode, half of the population N is randomly selected to be a vaccinator.

In the second stage, the time evolution of an epidemic season according to SIR dynamics is considered. Starting from I_0 agents, the initial infected patients are randomly selected from N agents and infection spreads through the agent network. Via the Gillespie algorithm [16] following SIR dynamics, the population is divided into sensitive agents, S, infected agents, I, and recovered agents, R, at a certain moment in the season. We assume an infection rate of β [day^{-1} person^{-1}] and a recovery rate of γ [day^{-1}]. If a non-vaccinator gets infected, he/she must pay a disease cost of C_i'. Without losing generality, we define the relative vaccination cost as $C_r = C_v/C_i$ ($0 \le C_r \le 1$; $C_i = 1$) for convenience. An epidemic season continues until all infected agents recover, meaning no infected patients exist in the domain. Table 1 gives the payoff matrix of our model.

2.2. Strategic adaptation

In the vaccination campaign, each agent revises his/her own strategy by reflecting on what happened around him/her during the previous epidemic season. We assume that strategy update takes place synchronously.

As a default method of strategic adaptation, we follow the assumptions of Fu et al. [6] as well as Fukuda et al. [7]. Agent i randomly selects agent j from his neighbors. Let us assume that their payoffs are π_i and π_j, respectively. The probability of agent i copying agent j's strategy, s_j, either vaccination or non-vaccination, instead of his own strategy, s_i, is $P\left(s_i \leftarrow s_j\right)$, which is defined as

$$P(s_i \leftarrow s_j) = \frac{1}{1+\exp[(\pi_i - \pi_j)/\kappa]}, \tag{1}$$

where κ indicates the sensitivity to the gain difference. Throughout our study, we assumed $\kappa = 0.1$. This update rule is called the Pairwise Fermi (PW-Fermi) comparison [17].

In this study, instead of "copying probability from one of the neighbors," we directly give an agent a "probability of committing vaccination," P_C, triggered by his consciousness of how dangerous it is to ignore vaccination. Namely,

$$P_C = \frac{1}{1+\exp[(C_r - < C_D >)/\kappa]}, \tag{2}$$

$$< C_D >= \frac{C_i \cdot n_i + C_f \cdot n_f}{n_D} \tag{3}$$

where C_i= 1 is the cost of being infected, C_f is the cost of free riding, which is zero, and n_D, n_i, and n_f are the numbers of non-vaccinators, infected agents, and free riders, respectively, in the agent's neighborhood. Therefore, $n_D = n_i + n_f$. $< C_D >$ indicates the average payoff of non-vaccinators in agent i's neighborhood.

One problem that arises is how to evaluate Eq. (3) if there are no non-vaccinators in agent i's neighborhood. We establish the following four cases as our sub-model.

Case 1 : Agent i retains his/her strategy.
Case 2 : As a substitute, we assume that $P_C = 1 - C_r$.
Case 3 : Agent i switches to the strategy opposite his/hers.
Case 4 : Substituting $<C_D>= 0$, we continue to rely on Eq. (2).

Case 1 expresses the fact that people tend to maintain the status quo. Case 2 assumes that an agent relies on the vaccination cost as alternative information. Case 3 assumes that an agent tends to take an inverse strategy if he/ she is stalemated due to lack of information. Case 4 assumes that an agent behaves in an optimistic manner by assuming that free riders can be successful.

2.3. Simulation method

We assume that $N = 4900$ and $I_0 = 5$. According to Fukuda et al. [7], we also assume that $\beta = 0.46$ and $\gamma = 1/3$ (the flu is assumed). In a simulation episode, one time-step consisting of the first stage, a vaccination campaign and the second stage, and an epidemic season continues until 3000 time-steps have passed. In a simulation study with varying relative vaccination cost, C_r, we observe the average vaccination coverage and final epidemic size in the last 1000 time-steps. The statistics shown below are based on 100 independent simulation episodes.

3. Results and discussion

In Fig. 1, we show (A) the vaccination coverage, (B) the final epidemic size, and (C) the average social payoff versus the vaccination cost, C_r. Except at $C_r = 0$, our new adaptation model shows higher vaccination coverage, therefore, leading to smaller final epidemic sizes than seen in the default model. However, note that, as far as the social payoff is concerned, Cases 3 and 4 show worse performance than both Cases 1 and 2 for the range of reasonable vaccination cost, although they seem better than the default case showing.

To further examine the results, Fig. 2 shows a typical time evolution of the 100 realizations for the last 100 time-steps prior to quasi-equilibrium in each case (Fig. 2(B–E)) with the default model (Fig. 2(A)) assuming $C_r = 0.3$. In the default case, as a general tendency, we see that larger final epidemic sizes with small time-fluctuations (compare Case 1 (Fig. 2(B)) and Case 2 (Fig. 2(C)) result from lower but more stable vaccination coverage. Conversely, in Case 2 and more clearly observed in Case 1, relatively higher and stable vaccination coverage successfully results in stably lower final epidemic sizes. Interestingly, the situation we observe in Case 3 (Fig. 2(D)) and Case 4 (Fig. 2(E)) is quite different. Significant time-fluctuations in both the vaccination coverage and the final epidemic size occur. This time-fluctuation seem to be two time-step periodic dynamics, as confirmed below. This fluctuation may cause the unwilling result in terms of "vaccination effectiveness" mentioned above, because it brings a lower social payoff than the default model despite higher vaccination coverage and lower final epidemic size on average for $0.3 \le C_r \le 0.6$.

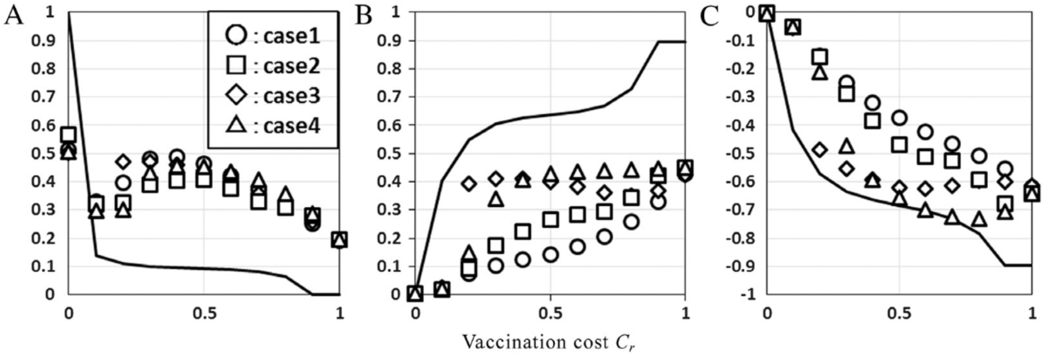

Fig. 1. Relationship between the vaccination cost and (A) the vaccination coverage, (B) the final epidemic size, and (C) the average social payoff for each of the four cases. Different symbols indicate the four cases, while the solid line indicates the result of the default setting according to Fu et al. [5].

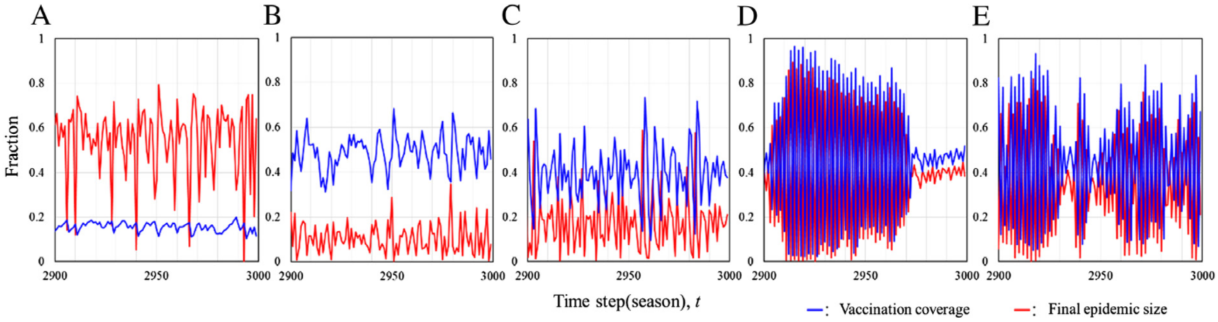

Fig. 2. Time evolution of the vaccination coverage (blue) and the final epidemic size (red) assuming $C_r = 0.3$: (A) Default case, (B) Case 1, (C) Case 2, (D) Case 3, and (E) Case 4.

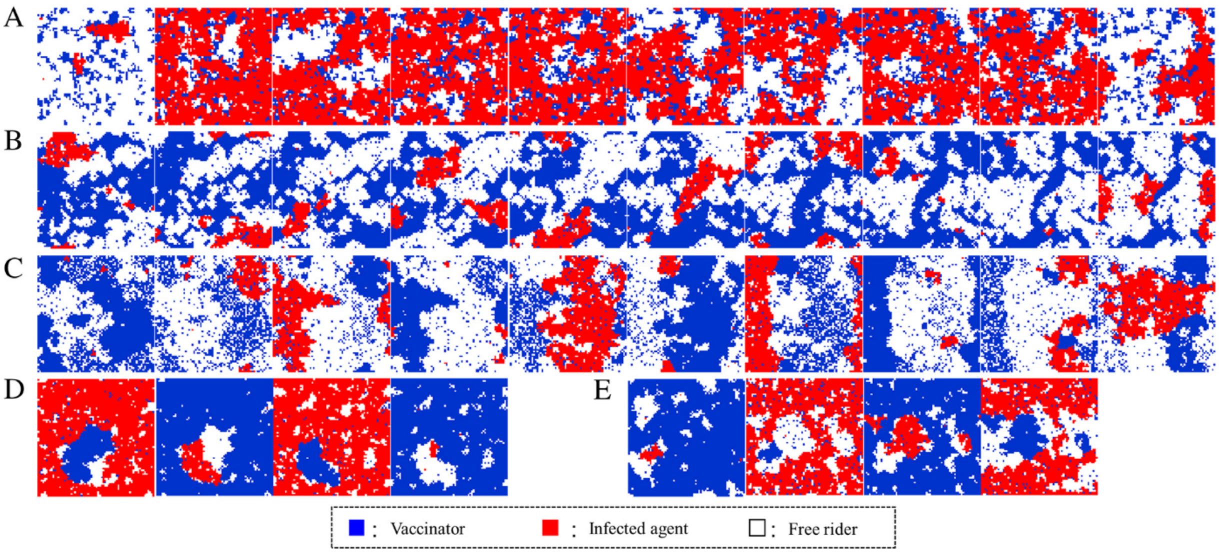

Fig. 3. Snapshots after 2940 time-steps assuming $C_r = 0.3$: (A) Default case, (B) Case 1, (C) Case 2, (D) Case 3, and (E) Case 4.

Fig. 3 offers further insight by showing continuous snapshots after 2940 time-steps for each of the four cases. Obviously, Case 3 (Fig. 3(D)) and Case 4 (Fig. 3(E)) show two time-step periodic flipping in which a situation with vaccinators with a small number of infected agents who failed to free ride follows a situation with infected agents with a small number of vaccinators. This inevitably results in a pandemic-like situation in Case 1 (Fig. 3(B)) and Case 2 (Fig. 3(C)) every other time-step, because the majority of vaccinators form small vaccinator-clusters and are less-spatially spread over the entire domain.

One plausible reason why these settings, especially those of Case 4, bring about such acute two time-step flipping can be thought of as follows. From the inherent nature of its definition, Case 4 sees the non-vaccination strategy as being more advantageous than the vaccination strategy if there are no infected neighbors. Our model framework in not only Case 4 but also in other cases urges infected agents to adopt a vaccinate strategy in the next time-step. This implies that agents in Case 4 tend to adopt the defective strategy (non-vaccination) if the outcome of the current time-step is good, while they adopt a cooperative strategy (vaccination) if the outcome of the current time-step is bad. This specific feature consequently results in the time flipping that was also observed in Win-Stay and Lose-Shift (WSLS) [18,19] of PD games and is a typical self-reflecting strategy (taking either the same offer or an opposing offer to the current) unlike the copying-from-others' strategy seen in Tit-for-Tat. As we confirmed above, Cases 3 and 4 contain some fragments of a "self-reflecting strategy." One recent study [20] reports that some strategic adaptations based on the concept of WSLS can enhance cooperation for spatial PD games. This is because sparsely located cooperative agents showing time-flipping manners with time-alternating defection are able to realize a reasonable amount of mutual reciprocity. This is interesting because the mechanism appears to be very different from the usual network reciprocity, as it was previously understood, in which a situation of compactly clustered cooperators would be more likely to result in efficient network reciprocity. However, in the vaccination game, which has a different game structure than PD games, some of our models, Cases 3 and 4, somehow contain a "self-reflecting" feature that does not result in any preferable consequences.

Unlike Cases 3 and 4, Cases 1 and 2 are able to achieve a preferable consequence, where a higher social payoff is established than that in the case of the default model. Fig. 3(B) and 3(C) indicate that, in both cases, quite a few vaccinators are sparsely located and, as consequence, vaccinators can ubiquitously exist in any corner of the domain. This is crucially important to oppress the spread of epidemics [21].

4. Conclusions

In this study, we established a new strategy adaptation idea in the vaccination game. Our update rule does not provide a "copying probability" from a focal agent's neighbor, as in conventional models; rather, it directly gives a "vaccination probability" derived from a stochastic comparison between the vaccination cost commonly disclosed in public and the expected benefit resulting from adopting the non-vaccination strategy observed in his/her neighborhood. We further define four subordinate models depending on how an agent behaves if he/she does not encounter a non-vaccinator among his/her neighbors.

The simulation results show that our new adaptation model generally results in higher vaccination coverage and smaller final epidemic sizes than those in the conventional model, which assumes social imitation of one of the neighbors.

However, depending on the subordinate models, there were two final consequences that either efficiently oppressed epidemic spreading or did not. Specifically, the case assuming that an agent that retains his/her strategy even if there are no neighboring defectors (non-vaccinators) (Case 1) allows vaccinators to be sparsely located in the domain, which can successfully hamper the spread of an epidemic in the domain. Conversely, the case assuming that an agent takes the reverse strategy if there are no defectors (Case 3) or assumes that a free ride will be successful if he/she has no defectors among his/her neighbors (Case 4) results in an acute time-flipping behavior, which allows huge pandemics every two time-steps.

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