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## ON OPTIMAL NON-RANDOM STATIONARY POLICIES IN FINITE STATE STOCHASTIC GAMES

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#### § 1. Introduction.

A stochastic game is determined by five objects: S, A, B, P, r. Here S is a state space of N points, 1, 2,  $\cdots$ , N; A is a set of actions available to Player I; B is a set of actions available to Player II; P is the low of motion of the system—it associates with each pair  $a \in A$ ,  $b \in B$  a trasition probability  $P_{ij}(a,b)$  for  $i,j \in S$ ; and r, the immediate reward, is a function on  $S \times A \times B$ . Throughout this paper we are concerned with the non-random Markov policies only, then a policy  $\pi$  for Player I is a sequence  $(f_1, f_2, \cdots)$ , where each  $f_n$  is a mapping from S into A, and the policy chooses an action  $f_n(i)$  in a state i at n-th day; a policy is said to be stationary if  $f_n = f$  for some mapping f from S into A for all n, and in this case  $\pi$  is denoted by  $f^{\infty}$ . A policy and a stationary policy for Player II are defined analogiously, and denoted by  $\sigma \equiv (g_1, g_2, \cdots)$  and  $\sigma \equiv g^{\infty}$  respectively.

Let  $X_1, X_2, \cdots$  be a Markov process on the state space S. The expected total reward with initial state i from a pair  $(\pi, \sigma)$  of policies for Player I and II is given by

$$I(\pi,\,\sigma)_i\equiv E\Big[\sum_{n=1}^\infty\beta^{n-1}r(X_n,\,f_n(X_n),\,g_n(X_n))\,|\,\pi\text{ and }\sigma\text{ are used and }X_1=i\Big]\,,$$

where  $\beta$  is a fixed discount factor,  $0 \le \beta < 1$ , such that a reward at n-th day in future is worth  $\beta^n$  times now. In the stochastic game, then, Player I wishes to choose  $\pi$  so that each component of the vector  $I(\pi,\sigma)=(I(\pi,\sigma)_i,\ i=1,\cdots,N)$  is maximized in some sense, and Player II wishes to choose  $\sigma$  so that  $I(\pi,\sigma)$  simultaneously minimized in some sense. A policy  $\pi^*$  is optimal for Player I if  $\inf_{\sigma}\sup_{\pi}I(\pi,\sigma)_i\le I(\pi^*,\sigma')_i$  for all  $\sigma'$  and  $i\in S$ , and a policy  $\sigma^*$  is optimal for Player II if  $\sup_{\sigma}I(\pi,\sigma)_i\ge I(\pi',\sigma^*)_i$  for all  $\pi'$  and  $i\in S$ . We shall say that the game is strictly determined if  $\sup_{\pi}\inf_{\sigma}I(\pi,\sigma)_i=\inf_{\sigma}\sup_{\pi}I(\pi,\sigma)_i$  for all  $i\in S$ .

Throughout this paper we impose the following assumptions: (A1) A and B are compact convex sets; (A2)  $P_{ij}(a,b)$  is a continuous and concave-convex function on  $A\times B$  for each pair  $i,j\in S$ ; (A3) r(i,a,b) is bounded on  $S\times A\times B$ , i. e.  $\sup_{i,a,b}|r(i,a,b)|$   $\equiv R<\infty$ , and for each fixed  $i\in S$ , is a continuous concave-convex function on  $A\times B$ .

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Under the assumptions stated above this paper shows that the game is strictly determined and that both players have optimal stationary policies. Furthermore a computational procedures for finding  $\varepsilon$ -optimal policies is given. Kushner and Chamberlain [1] treated these problems in the case where the policies feasible to both players were restricted to the stationary ones.

#### § 2. Some lemmas.

In this section we shall prove several lemmas concerning the expected total reward by virtue of new-defined operators. For each pair (f, g), where f is a mapping from S into A and g is from S into B, we define an operator  $L_{fg}$  on N-dimentional real vector space V as follows: for  $v \equiv (v_1, \dots, v_N) \in V$ ,

(2.1) 
$$L_{fg}v \equiv ((L_{fg}v)(i), i = 1, \dots, N),$$

where  $(L_{fg}v)(i) \equiv r(i, f(i), g(i)) + \beta \sum_{j=1}^{N} P_{ij}(f(i), g(i))v_j$ , for each  $i \in S$ . For each pair  $(\pi, \sigma)$  of policies we let

$$(2.2) I_n(\pi, \sigma; v) \equiv L_{f_1g_1}L_{f_2g_2}\cdots L_{f_ng_n}v, v \in V,$$

where  $L_{f_1g_1}L_{f_2g_2}v\equiv L_{f_1g_1}(L_{f_2g_2}v)$ . Denoting the vector  $(r(i,f(i),g(i)),\ i=1,\cdots,N)$  by r(f,g) and the  $N\times N$  matrix  $(P_{ij}(f(i),g(i)))$  by P(f,g), then, (2.2) can be expressed as follows:

(2.3) 
$$I_{n}(\pi, \sigma; v) = r(f_{1}, g_{1}) + \sum_{l=1}^{n-1} \beta^{k} \prod_{l=1}^{k} P(f_{l}, g_{l}) r(f_{k+1}, g_{k+1}) + \beta^{n} \prod_{l=1}^{n} P(f_{l}, g_{l}) v,$$

where  $\prod_{l=1}^k P(f_l, g_l) \equiv P(f_1, g_1) \cdots P(f_k, g_k)$ . Similarly  $I(\pi, \sigma)$  is expressed by

(2.4) 
$$I(\pi, \sigma) = r(f_1, g_1) + \sum_{k=1}^{\infty} \beta^k \prod_{l=1}^{k} P(f_l, g_l) r(f_{k+1}, g_{k+1}).$$

Lemma 2.1. (a)  $\sup_{\pi,\sigma}\|I(\pi,\,\sigma)\| \leq \frac{R}{1-\beta}, \text{ where } \|v\| = \max_{i} |v_i| \text{ for } v \in V.$ 

(b) For any  $v \in V$ ,  $I_n(\pi, \sigma; v)$  converges to  $I(\pi, \sigma)$  as  $n \to \infty$ .

PROOF. (a) Since by (A3)  $\sup_{i,a,b} |r(i,a,b)| = R < \infty$ , from (2.4)

$$\|I(\pi,\,\sigma)\| \leq \sum\limits_{k=0}^{\infty} eta^k R = rac{R}{1-eta}$$
 for any pair  $(\pi,\,\sigma)$  .

(b) From (2.3) and (2.4), for any  $\pi = (f_1, f_2, \dots)$  and  $\sigma = (g_1, g_2, \dots)$ ,

(2.5) 
$$I(\pi, \sigma) - I_n(\pi, \sigma; v)$$

$$=\beta^n \prod_{l=1}^n P(f_l, g_l) \Big\{ r(f_{n+1}, g_{n+1}) + \sum_{k=1}^\infty \beta^k \prod_{l=1}^k P(f_{n+l}, g_{n+l}) r(f_{n+k+1}, g_{n+k+1}) - v \Big\} \ .$$

Here, it is noted that the term in the brace in the righthand side of (2.5) expresses the expected total reward from the pair of policies  ${}^n\pi \equiv (f_{n+1}, f_{n+2}, \cdots)$  and  ${}^n\sigma \equiv (g_{n+1}, g_{n+2}, \cdots)$ . Hence, by (a) of Lemma 2.1,

$$\left\| r(f_{n+1}, g_{n+1}) + \sum_{k=1}^{\infty} \beta^k \prod_{l=1}^k P(f_{n+l}, g_{n+l}) r(f_{n+k+1}, g_{n+k+1}) \right\| \leq \frac{R}{1-\beta} .$$

Thus

$$\|I(\pi,\,\sigma) - I_n(\pi,\,\sigma\,;\,\,v)\| \leqq eta^n \Big(rac{R}{1-eta} + \|v\|\Big)$$
 ,

which yields that  $I_n(\pi, \sigma; v)$  converges to  $I(\pi, \sigma)$  as  $n \to \infty$ .

LEMMA 2.2. If both of f(a, b) and g(a, b) are concave-convex functions on  $A \times B$ , then  $\alpha f(a, b) + \alpha' g(a, b)$  is a concave-convex function on  $A \times B$  for  $\alpha, \alpha' \ge 0$ .

PROOF. This Lemma is clear from the definition of the concave-convex function on  $A \times B$ .

Next we give a minimax lemma useful for our stochastic game.

LEMMA 2.3. For any vector  $v = (v_1, \dots, v_N) \in V$ ,

(2.6) 
$$\max_{a} \min_{b} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b) v_{j} \right\}$$

$$= \min_{b} \max_{a} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b) v_{j} \right\} \quad \text{for all} \quad i \in S.$$

PROOF. By the assumptions (A1), (A2), (A3) and Lemma 2.2,  $r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b)(v_j + ||v||)$  is a continuous concave-convex function on  $A \times B$  for each  $i \in S$ . Then, by the general minimax theorem (cf. [4]), it holds that

(2.7) 
$$\max_{a} \min_{b} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b) (v_{j} + ||v||) \right\}$$
$$= \min_{b} \max_{a} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b) (v_{j} + ||v||) \right\} \quad \text{for all} \quad i \in S.$$

On the other hand, we get

(2.8) 
$$\max_{a} \min_{b} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b)(v_{j} + ||v||) \right\}$$
$$= \max_{a} \min_{b} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b)v_{j} \right\} + \beta ||v||,$$

and

(2.9) 
$$\min_{b} \max_{a} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b)(v_{j} + ||v||) \right\}$$

$$= \min_{b} \max_{a} \left\{ r(i, a, b) + \beta \sum_{j=1}^{N} P_{ij}(a, b)v_{j} \right\} + \beta ||v||, \quad \text{for all } i \in S.$$

Thus, from (2.7), (2.8) and (2.9), we get (2.6), which completes the proof.

Now we define an operator T on V as follows:

$$Tv \equiv ((Tv)(i), i = 1, \dots, N), v \in V$$

where  $(Tv)(i) \equiv \max_{a} \min_{b} \left\{ r(i, a, b) + \beta \sum_{i=1}^{N} P_{ij}(a, b) v_j \right\}$  for every  $i \in S$ .

LEMMA 2.4. The operator T is a contraction mapping on V, and has an unique fixed point  $v^* \in V$ , i.e.  $Tv^* = v^*$ .

PROOF. For vectors  $u, v \in V$ , plainly  $u \le v + ||u - v|| \mathbf{1}$ , where  $\mathbf{1}$  is the identity of

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V. Since it is clear from the definition that T is monotone,

$$Tu \le T(v + ||u - v||\mathbf{1}) = Tv + \beta ||u - v||\mathbf{1}$$
,

and consequently,  $Tu-Tv \le \beta \|u-v\|\mathbf{1}$ . Similarly  $Tv-Tu \le \beta \|u-v\|\mathbf{1}$ . Thus we get  $\|Tu-Tv\| \le \beta \|u-v\|$ , which shows that T is a contraction mapping on V because of the discount factor  $\beta$ .

Since V is the Banach space with the supremum norm, T has an unique fixed point  $v^* \in V$  by virtue of the Banach fixed-point theorem. Thus the Lemma is proved.

#### § 3. Optimal stationary policies.

In this section we give our main theorem, the existence of optimal stationary policies. The proof of it is very constructive.

THEOREM 3.1. The game is strictly determined, and players I and II have optimal stationary policies.

PROOF. By the assumptions (A1), (A2), (A3) and lemmas 2.2, 2.3, it holds that

$$\begin{split} v_i^* &= \max_a \, \min_b \, \left\{ r(i,\,a,\,b) + \beta \sum_{j=1}^N P_{ij}(a,\,b) v_j^* \right\} \\ &= \min_b \, \max_a \, \left\{ r(i,\,a,\,b) + \beta \sum_{j=1}^N P_{ij}(a,\,b) v_j^* \right\} \qquad \text{for all} \quad i \in S \;, \end{split}$$

and furthermore there exist two sequences  $\{a_i \in A, i=1, \dots, N\}$  and  $\{b_i \in B, i=1, \dots, N\}$  such that

(3.1) 
$$v_i^* = \min_b \left\{ r(i, a_i, b) + \beta \sum_{j=1}^N P_{ij}(a, b) v_j^* \right\}$$

$$= \max_a \left\{ r(i, a, b_i) + \beta \sum_{j=1}^N P_{ij}(a, b) v_j^* \right\} \quad \text{for all} \quad i \in S.$$

We now define the functions  $f_*$  from S into A and  $g_*$  from S into B by

$$f_*(i) \equiv a_i$$
,  $g_*(i) \equiv b_i$  for each  $i \in S$ .

Then (3.1) is expressed as follows:

(3.2) 
$$v_i^* = \min_b \left\{ r(i, f_*(i), b) + \beta \sum_{j=1}^N P_{ij}(f_*(i), b) v_j^* \right\}$$

$$= \max_a \left\{ r(i, a, g_*(i)) + \beta \sum_{j=1}^N P_{ij}(a, g_*(i)) v_j^* \right\} \quad \text{for } i \in S.$$

Let fix  $i \in S$  arbitrary. For any policies  $\pi = (f_1, f_2, \cdots)$  and  $\sigma = (g_1, g_2, \cdots)$ , by (2.1) and (3.2),

$$\begin{split} v_i^* & \leq r(i, f_*(i), g_n(i)) + \beta \sum_{j=1}^N P_{ij}(f_*(a), g_n(i)) v_j^* \\ &= (L_{f_*g_n} v^*)(i) \;, \\ v_i^* & \geq r(i, f_n(i), g_*(i)) + \beta \sum_{j=1}^N P_{ij}(f_n(i), g_*(i)) v_j^* \\ &= (L_{f_ng_*} v^*)(i) \;, \qquad \text{for all} \quad n \geq 1 \;. \end{split}$$

Since  $L_{f \cdot g_n}$  and  $L_{f_n g \cdot}$  are monotone for each  $n \ge 1$ , as are easily shown by its definition,

$$\begin{split} v_i^* & \leq (L_{f * g_1} L_{f * g_2} \cdots L_{f * g_n} v^*)(i) = I_n(f_*, \sigma \colon v^*)_i \,, \\ v_i^* & \geq (L_{f_1 g} L_{f_2 g} \cdots L_{f_n g}, v^*)(i) = I_n(\pi, g_* \colon v^*)_i \,, \qquad \text{for all} \quad n \geq 1 \,, \end{split}$$

where  $I_n(\pi, \sigma: v) \equiv (I_n(\pi, \sigma: v)_i, i = 1, \dots, N)$ . By Lemma 2.1 (b),  $I_n(f_*^{\infty}, \sigma: v^*)$  converges to  $I(f_*^{\infty}, \sigma)$  and  $I_n(\pi, g_*^{\infty}: v^*)$  to  $I(\pi, g_*^{\infty})$  as  $n \to \infty$ . Hence

$$I(\pi, g_*^{\infty})_i \leq v_i^* \leq I(f_*^{\infty}, \sigma)_i$$
.

Since  $\pi$ ,  $\sigma$  and  $i \in S$  are arbitrary,

$$\sup_{\pi} I(\pi, g_{*}^{\infty})_{i} \leq v_{i}^{*} \leq \inf_{\sigma} I(f_{*}^{\infty}, \sigma)_{i}, \quad \text{for all} \quad i \in S.$$

Then we have

$$\begin{split} \inf_{\sigma} \sup_{\pi} I(\pi,\,\sigma)_i & \leq \sup_{\pi} I(\pi,\,g_{\,*}^{\,\infty})_i \\ & \leq \inf_{\sigma} I(f_{\,*}^{\,\infty},\,\sigma)_i \\ & \leq \sup_{\pi} \inf_{\sigma} I(\pi,\,\sigma)_i \quad \text{ for all } \quad i \in S \,. \end{split}$$

Generally it is true that

$$\inf_{\sigma} \sup_{\pi} I(\pi, \sigma)_i \ge \sup_{\pi} \inf_{\sigma} I(\pi, \sigma)_i \quad \text{for all} \quad i \in S.$$

Therefore we have

$$\inf_{\sigma} \sup_{\pi} I(\pi, \sigma)_i = \sup_{\pi} I(\pi, g_{*}^{\infty})_i$$

$$= \inf_{\sigma} I(f_{*}^{\infty}, \sigma)_i$$

$$= \sup_{\pi} \inf_{\sigma} I(\pi, \sigma)_i \quad \text{for all} \quad i \in S.$$

Thus our game is strictly determined, and  $f_*^{\infty}$  and  $g_*^{\infty}$  are optimal stationary policies for Player I and Player II respectively.

#### § 4. Computational procedures of $\varepsilon$ -optimal policies.

Let  $v^{0}$  be any vector of V and we shall define the sequence  $\{v^{n}, n=1, 2, \cdots\}$  by

$$v^n \equiv Tv^{n-1}$$
,  $n=1, 2, \cdots$ ,

where T is the operator defined in § 2.

LEMMA 4.1. The sequence  $\{v^n, n=1, 2, \cdots\}$  converges to  $v^*$  which is the fixed point of the operator T.

PROOF. By the definition of T,

$$||v^n - v^{n+1}|| \le \beta^n ||v^0 - Tv^0|| \quad \text{for all} \quad n \ge 1,$$

hence  $\{v^n\}$  is a Caucy-sequence. Thus  $\{v^n, n=1, 2, \cdots\}$  converges to  $v^*$ , for V is a Banach space and T has an unique fixed point  $v^*$ .

THEOREM 4.1. Fix any  $\varepsilon > 0$ . Then, for sufficiently large n such that

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$$\beta^n \leq \frac{(1-\beta)^2 \varepsilon}{3 \|v^0 - Tv^0\|},$$

it holds that

$$\|v^n - v^*\| \leq \frac{(1 - \beta)\varepsilon}{3}$$
 ,

and we can choose  $f_{n(\varepsilon)}$  and  $g_{n(\varepsilon)}$  such that

$$\begin{split} &I(\pi',\,g_{\,n(\epsilon)}^{\,\infty})_i - \epsilon \leqq \sup_{\pi} \inf_{\sigma} \, I(\pi,\,\sigma)_i \qquad \textit{for all} \quad \pi' \ \textit{and} \ i \in S \,, \\ &I(f_{\,n(\epsilon)}^{\,\infty},\,\sigma')_i + \epsilon \geqq \inf_{\sigma} \sup_{\sigma} \, I(\pi,\,\sigma)_i \qquad \textit{for all} \quad \sigma' \ \textit{and} \ i \in S \,. \end{split}$$

[This shows that  $f_{n(\varepsilon)}^{\infty}$  and  $g_{n(\varepsilon)}^{\infty}$  are  $\varepsilon$ -optimal policies for Players I and II respectively]. PROOF. By Lemma 4.1 and (4.1),

$$\begin{split} \|v^n - v^*\| & \le \beta^n \|v^0 - Tv^0\| (1 + \beta + \cdots) \\ & = \frac{\beta^n \|v^0 - Tv^0\|}{1 - \beta} \; . \end{split}$$

Then trivially

$$||v^n - v^*|| \le \frac{(1 - \beta)\varepsilon}{3}$$

for sufficiently large n for which (4.2) holds, and similarly

(4.4) 
$$||v^{n+1} - v^*|| \le \frac{(1-\beta)\varepsilon}{3}$$
.

By Lemma 2.3 and the definitions of  $\{v^n, n=1, 2, \cdots\}$  and of T, there exist  $\{a_i \in A, i=1, \cdots, N\}$  and  $\{b_i \in B, i=1, \cdots, N\}$  such that

$$(4.5) v_i^{n+1} \leq \min_b \left\{ r(i, a_i, b) + \beta \sum_{i=1}^N P_{ij}(a_i, b) v_j^n \right\} + \frac{(1-\beta)\varepsilon}{3} ,$$

$$(4.6) v_i^{n+1} \ge \max_a \left\{ r(i, a, b_i) + \beta \sum_{j=1}^N P_{ij}(a, b_i) v_j^n \right\} - \frac{(1-\beta)\varepsilon}{3}.$$

Now we define the functions  $f_{n(\varepsilon)}: S \to A$  and  $g_{n(\varepsilon)}: S \to B$  by

$$f_{n(\varepsilon)}(i) \equiv a_i$$
,  $g_{n(\varepsilon)}(i) \equiv b_i$ , for  $i = 1, \dots, N$ .

By (4.3), (4.4), (4.5) and (4.6), then we have

$$(4.7) r(i, a, g_{n(\varepsilon)}(i)) + \beta \sum_{j=1}^{N} P_{ij}(a, g_{n(\varepsilon)}(i)) v_{j}^{*} - (1-\beta)\varepsilon$$

$$\leq v_{i}^{*} \leq r(i, f_{n(\varepsilon)}(i), b) + \beta \sum_{j=1}^{N} P_{ij}(f_{n(\varepsilon)}(i), b) v_{j}^{*} + (1-\beta)\varepsilon,$$

for all  $a \in A$ ,  $b \in B$  and  $i \in S$ . The above inequality (4.7) implies that for any function f and g

$$(L_{fg_{R(\varepsilon)}}v^*)(i)-(1-\beta)\varepsilon \leqq v_i^* \leqq (L_{f_{R(\varepsilon)}g}v^*)(i)+(1-\beta)\varepsilon \ .$$

Then, for any policies  $\pi = (f_1, f_2, \dots), \sigma = (g_1, g_2, \dots)$  and for any integer  $m \ge 1$ ,

$$\begin{split} I_m(\pi, g_{n(\varepsilon)}^{\infty} : v^*)_i - (1 - \beta)\varepsilon(1 + \beta + \cdots + \beta^{m-1}) \\ &\leq v_i^* \leq I_m(f_{n(\varepsilon)}^{\infty}, \sigma : v^*)_i + (1 - \beta)\varepsilon(1 + \beta + \cdots + \beta^{m-1}) \;. \end{split}$$

By Lemma 2.1 (b)

$$I(\pi, g_{n(\varepsilon)}^{\infty})_i - \varepsilon \leq v_i^* \leq I(f_{n(\varepsilon)}^{\infty}, \sigma)_i + \varepsilon$$
,

for all  $\pi$ ,  $\sigma$  and  $i \in S$ . By appealing to the proof of Theorem 3.1 we have  $v_i^* = \sup_{\pi} \inf_{\sigma} I(\pi, \sigma)_i = \inf_{\sigma} \sup_{\pi} I(\pi, \sigma)_i$  for all  $i \in S$ . Thus we find that  $f_{n(\varepsilon)}$  and  $g_{n(\varepsilon)}$  satisfy the inequalities required in the theorem.

#### References

- [1] H. J. Kushner and S. G. Chamberlain, Finite state stochastic games: Existence theorems and Computational procedures, IEEE. Trans. Automatic Control, Vol. AC-14, No. 3, June. 1969.
- [2] R. E. Strauch, Negative dynamic programming, Ann. Math. Statist. Vol. 37, 1966.
- [3] T. Parthasarathy and T. S. E. Raghavan, Some topics in Two-Person Games, American Elsevier, New York, 1971.
- [4] S. Karlin, Mathematical Methods and Theory in Games: Programming and Economics, Vol. II, Addison-Wesley, London, 1959.