Depth Limited Treatment Planning and Scheduling for Electronic Triage System in MCI

Ayaka Kashiyama, Akira Uchiyama, and Teruo Higashino

Graduate School of Information Science and Technology, Osaka University,
1-5 Yamadaoka, Suita, Osaka 5650871, Japan
{a-kasiym,utiyama,higashino}@ist.osaka-u.ac.jp

Abstract. For supporting rescue operations in disasters, vital data collections in wireless sensor networks have been proposed so far. In such systems, we can expect to predict each patient's probability of survival based on real-time vital data. In this paper, we focus on prehospital care and propose a method to determine treatment plans and schedules of patients. The proposed method maximizes the number of expected saved patients under limited medical resources. This optimization problem is called Treatment Planning and Scheduling, which is NP-hard. Therefore, we propose a heuristic algorithm based on depth-limited search. We have compared the proposed method with greedy methods. The results show the proposed method can derive solutions in practical time and the average number of saved patients is 10% larger compared to the greedy methods.

Keywords: Mass Casualty Incident, Disaster Medical Care, Treatment Planning and Scheduling, NP-hard, Depth Limited Search.

1 Introduction

Triage is a process of prioritizing patients based on vital signs in Mass Casualty Incidents (MCIs) such as earthquakes and terrorism. The purpose of triage is to save as many patients as possible under limited medical resources, e.g. medical supplies and physicians. Our research group has been developing an electronic triage system called eTriage which uses wireless networks for supporting rescue and medical operations in disasters[1]. We have developed an electronic triage tag to measure a heart rate and a blood oxygen level of a patient. The electronic triage tag is capable of ZigBee communication, and wireless sensor networks are built over the tags attached to patients. Through monitoring patients' vital signs, a sudden change of each patient's condition is notified to healthcare workers. Similarly, AIDN(Advanced Health and Disaster Aid Network)[2] and WIISARD (Wireless Internet Information System for Medical Response in Disasters)[3] also investigate an advanced medical support system by using wireless networks.

Moreover, some medical research works have proposed methods for predicting patient survivability. For example, TRISS method[4] predicts the probability of

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survival of a patient from the ISS (Injury Severity Score) and the RTS (Revised Trauma Score) calculated from anatomic, physiologic, and age characteristics. Such survivability prediction is expected to become more accurate and sophisticated in the future by collecting a large amount of vital data with the aid of ICT (Information and Computer Technology). Then, precise triage based on real-time vital data of patients will be possible.

There are some methods using ICT for supporting rescue operations in MCIs. Ref.[5] proposes a transportation scheduling algorithm from a disaster site to multiple hospitals to maximize total survivability of patients assuming future advanced survivability prediction. Ref.[6] presents an agent-based scheduling algorithm for patients in a hospital. However, in order to maximize the number of saved patients in MCIs, we need consider a large variety of operations including transportation and medical treatments in both a disaster site and a hospital.

In this paper, we focus on prehospital care in MCIs and propose a method to derive treatment plans and schedules of patients that maximize the number of saved patients under the assumption that accurate prediction of survivability is possible. For this purpose, we model prehospital care in MCIs as shown in Fig. 1 based on the Emergo Train System (ETS)[7], which is a widely used on-the-desk simulation toolkit for disaster medical care exercises in hospitals. Given conditions of each patient, we need decide treatment plans and schedules under limited medical resources. Deadlines and essential treatments for each patient are also given, and if essential treatments of a patient do not finish before the deadline, the patient is considered to die.

Our goal is to maximize the number of saved patients in this ETS-based disaster medical care model. We call this maximization problem as a Treatment Planning and Scheduling (TPS) problem, of which a sub-problem is equivalent to an Integrated Process Planning and Scheduling (IPPS) problem, known as NP-hard[8]. To solve TPS problem, we need choose treatment plans for each patient. For example, some patients may be treated completely in the disaster site and some others may be transported to the hospital without treatment. It may also increase the number of saved patients to treat some patients partly in the disaster site, which results in extensions of the patients' deadlines. Furthermore, after determining treatment plans, we need decide the treatment order of patients who use the same medical resources such as ambulances and physicians. As we mentioned above, deadlines of patients change if such treatment plans are chosen. On the other hand, deadlines are fixed and do not change depending on chosen plans in IPPS problems. For this reason, TPS problems are more complicated than IPPS problems and we cannot directly apply methods for IPPS[9,10] to TPS. Ref. [11] considers penalty functions over time to consider degradation of condition and proposes an algorithm for optimizing medical supply in disaster scenarios to minimize the total penalty. Our approach aims to treat as many patients as possible before deadlines and does not consider waiting time for treatment. In this sense, Ref. [11] is different from our approach.

Since TPS is difficult than NP-hard problem, we propose a heuristic algorithm using depth limited search to solve TPS problems in practical time. To the best of

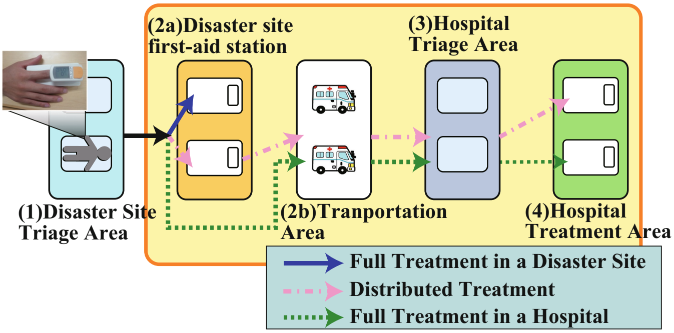

Fig. 1. Overview of Disaster Medical Care

our knowledge, there is no research on determining treatment plans and schedules of patients in MCIs focusing on the early stage of disaster medical care.

We have compared the proposed method with two deadline-based greedy methods for evaluation. The results show that the proposed method derives solutions that save approximately 10% more patients than the greedy methods in a few seconds.

2 Treatment Planning and Scheduling Problem

2.1 Assumptions and Disaster Medical Care Model

We assume our electronic triage tags are attached to all patients in a disaster site, and vital signs of the patients are transmitted to a server via wireless ad hoc networks. The changes of patient's survivability over time are predicted based on the collected vital data at the server. We also assume the server knows the numbers of patients that each area can treat/transport in parallel based on medical resource information such as the numbers of physicians, nurses, and ambulances. Then, our method determines how and in which order the patients should be treated.

Figure 1 shows the overview of the modeled disaster medical care. Hereafter, we target a case of a single hospital for simplicity of discussion. However, note that modeling of a case of multiple hospitals is also possible in the same manner. In this model, we assume that we cannot interrupt a treatment once it starts, and that multiple patients are not allowed to be treated by using the same medical resource simultaneously. We assume there are five areas as follows, and patients are treated at each area and transported to the next area as necessary.

1. Disaster site triage area: Firstly, every patient is moved from a disaster site to this area. In this area, electronic triage tags are attached to each patient on a First-Come, First-Served (FCFS) basis to monitor their vital signs.

2a. Disaster site first-aid station: Physicians and nurses treat patients in the disaster site.

Table 1. Notations Used for Formulation

Symbol	Explanation
P	A set of patients
M	A set of medical resources
R	A set of treatment plans
c_h^r	The hth operation in process plan r
$t_i[c_h^r, m]$	Required time for patient i's operation c_h^r using medical resource m
$T_i[c_h^r, m]$	Completion time of patient i's operation c_h^r using medical resource m
$d_i[c_h^r, m]$	Deadline of patient i's operation c_h^r using medical resource m
X_i^r	$\begin{cases} 1, \text{if treatment plan } r \text{ is selected for patient } i \\ 0, \text{otherwise} \end{cases}$
$Y_m[i, j, c_h^r, c_g^s]$	$\begin{cases} 1, \text{ if patient } i\text{'s operation } c_h^r \text{ precedes patient } j\text{'s operation } c_g^s \text{ on medical resource } m \\ 0, \text{ otherwise} \end{cases}$
$Z_i[c_h^r, m]$	$\begin{cases} 1, \text{ if medical resource } m \text{ is selected for patient } i\text{'s operation } c_h^r \\ 0, \text{ otherwise} \end{cases}$

2b. Transportation area: Patients are transported from the disaster site to a hospital by ambulances.
3. Hospital triage area: Conditions of patients are checked again. After that they are transported to a treatment area in the hospital.
4. Hospital treatment area: Physicians and nurses treat patients in the hospital. Usually, medical resources in the hospital are much more than those in the disaster site.

At first, an electronic triage tag is attached to a patient at (1) a disaster site triage area. Then, the patient is transported to the next area, which is either (2a) the disaster site first-aid station or (2b) a transportation area, depending on each patient's treatment plan. We can treat the patient by using medical resources in (2a) a disaster site first-aid station and (4) a hospital treatment area. After transportation by an ambulance, the patient has to be checked his condition at (3) the hospital triage area before transportation to (4) the hospital treatment area.

We assume there are two types of treatments: full treatment and distributed treatment. For each case, time required to finish treatment and deadlines for these treatments are given, and we need finish either of the treatment by the given deadline in order for saving the patient. Full treatment finishes patient's treatment at either the disaster site first-aid station or the hospital treatment area. On the other hand, in distributed treatment, we firstly treat a patient at the disaster site to prolong the deadline, transport the patient to the hospital, and then finish the remaining treatment in the hospital. Therefore, there are three treatment plans as shown by the arrows in Fig. 1.

2.2 Problem Formulation

We formulate TPS problem based on Ref.[11] which formulates Integrated Process Planning and Scheduling (IPPS) problem. Table 1 shows notations used in the formulation. There are $|R|$ treatment plans, and the sequence of operations for selected treatment plan $r \in R$ is denoted as $c_1^r, c_2^r, \ldots, c_{|r|}^r$. These operations include medical treatments such as full treatment and distributed treatment, and we regard transportation by an ambulance as one of the operations as well. For each patient i, time required to complete operation c_h^r by using medical resource $m \in M$ is given and denoted by $t_i[c_h^r, m]$ where M is a set of medical resources.

There are three constraints, that are (i) a treatment plan selection constraint, (ii) an operation sequence constraint, and (iii) an interruption constraint. Firstly, the equation (1) shows the treatment plan selection constraint which indicates each patient must select exactly one treatment plan.

$$\sum_{r=1}^{R} X_i^r = 1 \qquad \forall i \in P \tag{1}$$

where P is a set of patients and X_i^r represents the selection state of treatment plan r for patient i.

Secondly, the operation sequence constraint is described as shown in the expression (2). This constraint means the sequence of operations must follow the sequence of operations $c_1^r, \ldots, c_{|r|}^r$ in treatment plan r if treatment plan r is selected for patient i.

$$\begin{aligned} X_i^r \times (Z_i[c_h^r, m_1] \times T_i[c_h^r, m_1] - Z_i[c_{h-1}^r, m_2] \times T_i[c_{h-1}^r, m_2]) \\ \geq X_i^r \times t_i[c_h^r, m_1] \times Z_i[c_h^r, m_1] \\ \forall i \in P, \quad \forall r \in R, \quad \forall m_1, m_2 \in M, \quad \forall h \in [2, |r|] \end{aligned} \tag{2}$$

Here, $T_i[c_h^r, m]$ is completion time of operation c_h^r for patient i by using medical resource m. $Z_i[c_h^r, m]$ indicates the selection state of medical resource m for operation c_h^r of patient i.

Finally, the interruption constraint is represented by the expression (3). This constraint indicates medical resources cannot handle two or more operations simultaneously and no operation is interrupted by other operations once it starts. A state binary $Y_m[i, j, c_h^r, c_g^s]$ represents the sequence of patient i's operation c_h^r and patient j's operation c_g^s that use the same machine m.

$$\begin{aligned} Y_m[i, j, c_h^r, c_g^s] \times (T_j[c_g^s, m] - T_i[c_h^r, m]) \geq Y_m[i, j, c_h^r, c_g^s] \times t_i[c_h^r, m] \\ \forall i, j \in P, \quad \forall r, s \in R, \quad \forall h \in [1, |r|], \quad \forall g \in [1, |s|], \quad \forall m \in M \end{aligned} \tag{3}$$

For simplicity, we introduce another state binary D_i^r as follows, which indicates whether all operations of patient i finish before the deadlines on treatment plan r or not.

$$D_i^r = \begin{cases} 1, \text{ if } Z_i[c_h^r, m] \times (d_i[c_h^r, m] - T_i[c_h^r, m]) < 0 \\ \qquad\qquad \forall h \in [1, |r|], \quad \forall m \in M \\ 0, \text{ otherwise} \end{cases} \tag{4}$$

Then, the objective function is defined as the following expression (5) that minimizes the number of deaths, which is equivalent to maximizing the number of saved patients.

$$\text{minimize} \sum_{i \in P} D_i^r \times X_i^r \quad \forall r \in R \tag{5}$$

Subject to: (1), (2), and (3).

3 Depth Limited Treatment Planning and Scheduling

3.1 Overview

In TPS problem, we need determine both treatment plans X_i^r and schedules $Y_m[i, j, c_h^r, c_g^s]$ for all patients. Schedules are determined for each area while treatment plans are selected right before the disaster site first-aid station because treatment plans branch after a patient is rescued from the disaster site.

For scheduling at each area, we apply deadline-based greedy scheduling because the more serious condition a patient is, the higher the patient's treatment priority is. However, there is possibility that we can save two or more patients by abandoning one patient. For example, a seriously injured patient may take long time for treatment, and if we treat the patient, other patients may die. Therefore, we explore such possibilities in addition to distributing medical workloads over the disaster site and the hospital. This means the number of treatment plans is four: (i) full treatment in the disaster site, (ii) distributed treatment in both the disaster site and the hospital, (iii) full treatment in the hospital, and (iv) abandonment.

3.2 Depth Limited Treatment Planning

We cannot solve TPS problem in practical time if we explore all combinations of treatment plans for all patients because it requires exponential time with respect to the number of patients. For this reason, we limit the number of patients to explore treatment plans. It is natural that exploring other plans of a seriously injured patient is more likely to improve the result. Hence we explore all plans of the k most serious patients with respect to deadlines, and choose such treatment plans for those k patients that maximize the number of saved patients. Hereafter, we describe a set of those k most serious patients with respect to deadlines in a set of patients P as P_k.

Given a candidate of treatment plans of k patients, we need assign treatment plans of the other patients in $P - P_k$ to compute the number of saved patients. We select treatment plans of the other patients in a greedy manner where full treatment in a disaster site is assigned. In this manner, we need not consider distributed treatment and abandonment for the patients in $P - P_k$, thus the computation time is reduced. Firstly, the proposed method sorts $|P|$ patients in ascending order right after the triage area. Secondly, it explores and determines top k patients' treatment plans. Then, we repeat the same process for the set of $P - P_k$ until the treatment plans of all patients are determined.

An example of the depth limited planning is shown in Fig. 2. Suppose there are 6 patients $A, B, \ldots, F$ in ascending order with respect to their deadlines. In this

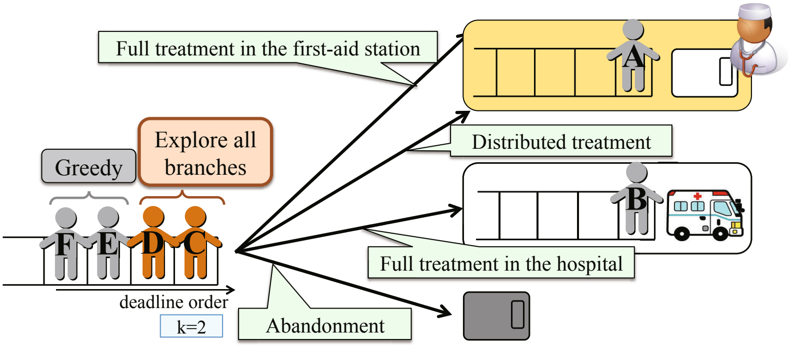

Fig. 2. Example of Depth Limited Treatment Planning

Table 2. Treatment Time and Deadlines Used in Simulation (sec.)

	Urgent	Priority	Delayed	Minimal
Treatment time t_f	[4000,5000]	[300,450]	[120,400]	[100,300]
Treatment time t_h	-	[300,450]	[200,400]	[300,500]
Deadline d	[100,900]	[780,1680]	[1700,3300]	[3300,6300]
Ext. deadline d'	-	[1000,1500]	[1000,2000]	[1000,2000]

example, we assume $k = 2$, and let treatment plans of A and B be determined as full treatment in the first-aid station and full treatment in the hospital, respectively. Then, the next k patients are C and D. We explore all treatment plans for C and D while treatment plans of E and F are selected greedily.

We also consider other criteria to derive a better solution. This is because it is likely to happen that the numbers of saved patients for different candidates are equal. In such cases, it is desirable to select the candidate which does not occupy medical resources in the disaster site as much as possible to keep medical resources available for the following patients. This means the proposed method prioritizes candidates with the maximum number of saved patients according to the following criteria: the number of abandoned patients, full treatment plans in the hospital, and distributed treatment plans. For example, suppose there are two candidates c_1 and c_2 with the maximum number of saved patients. If the number of abandoned patients in c_1 is larger than c_2, we select c_1 as the best treatment planning. If the numbers of abandoned patients are equal, the numbers of full treatment in a hospital are compared to determine the best planning.

4 Performance Evaluation

4.1 Settings

We have evaluated the performance of the proposed method through simulation. In the evaluation, we assume four categories: urgent, priority, delayed, and minimal. Particularly, deadlines of urgent patients are short while it takes long time to finish treatment. We have assigned patients one of the categories, and the treatment time and deadlines of the patients are randomly selected from the ranges shown in Table 2 according to their categories. Time required for distributed treatment is t_f in the first-aid station and t_h in the hospital. For treatment plans of full treatment, the time to complete the treatment operation is $t_f + t_h$ independently of treatment areas. Deadline d is extended by d' when distributed treatment is selected and the treatment operation in the first-aid station finished. We set the total number of patients to 100. We also set the numbers of patients that each area can handle simultaneously in the first-aid station, the transportation area, the hospital triage area, and the hospital treatment area to 6, 5, 7, and 21, respectively. We used a workstation with Intel Xeon 2.66 GHz and 23.6 GB memory for evaluation. The results are averages of 100 random cases.

We used two types of scenarios. The first one is a scenario with urgent patients, where there are 15 urgent, 40 priority, 35 delayed, 10 minimal patients, respectively. The second one is a scenario without urgent patients. For the scenario without urgent patients, we used 45 priority, 35 delayed, 20 minimal patients.

For comparison, we introduce two greedy approaches to determine treatment plans: a Disaster Site weighted greedy approach (DS-greedy) and a Hospital weighted greedy approach (H-greedy). The decision of DS greedy and H-greedy is different when (i) medical resources in the disaster site and the transportation area are available and (ii) medical resources in both areas are occupied. In the above two cases, DS-greedy selects full treatment in the disaster site while H-greedy selects full treatment in the hospital. In both greedy approaches, schedules are determined based on a FCFS basis. We have selected the above two approaches for comparison since we believe they are close to doctors' decision: doctors try to prioritize patients according to their conditions and treat them greedily with respect to the priorities.

4.2 Effect of Limited Depth k

To see the effect of depth k for limited search, we have measured computation time for different depth k in the scenario with urgent patients. The result is shown in Fig. 3. We can see the number of saved patients increases with the increase of k although computation time increases exponentially. This is because the number of combinations is $O(|R|^k)$ and in this case $|R| = 4$. It is obvious that there is a trade-off between computation time and the number of saved patients. From the result, $k = 4$ is the most balanced since the computation time is about 5 seconds and the result is comparable to that of $k = 5$. Therefore, we use $k = 4$ in the following evaluation.

4.3 Comparison with Greedy Methods

We have compared the proposed method with DS-greedy and H-greedy approaches in two simulation scenarios. Table 3 describes the results of the

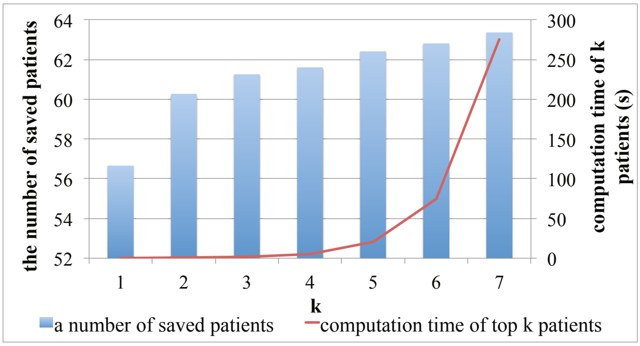

Fig. 3. Depth k vs. # of Saved Patients and Computation Time

Table 3. Comparison on the Number of Saved Patients with Greedy Methods

	DS-greedy	H-greedy	Proposed
Scenario w/ urgent patients	17.70	16.81	61.59
Scenario w/o urgent patients	65.82	65.89	74.93

comparison. The results show there is not much difference between two greedy methods. This is because there is not much difference between the amount of medical resources available in the first-aid station and the transportation area.

In the scenario with urgent patients, the number of the saved patients in the proposed method is more than three times of those in the greedy methods. The reason is that medical resources are occupied by urgent patients in the greedy methods since they do not abandon urgent patients those require long time for treatment. In contrast, the proposed method can derive better solutions because the proposed method explores possibilities of abandonment. Even in the scenario without urgent patients, the proposed method has achieved approximately 10% better result than the compared greedy approaches. This result indicates the effectiveness of distributing workload of the first-aid station and the hospital, which is explored by the proposed method. From the results, we have confirmed the proposed method can derive better solutions than the greedy methods by exploring all treatment plans for k patients.

5 Conclusion

In this paper, we modeled prehospital care and proposed a method to derive treatment plans and schedules of patients that maximize the number of saved patients in practical time under the assumption that accurate prediction of future probability of survival is possible. The proposed method uses depth-limited search to explore possibilities of improvement. We evaluated the proposed method through simulation and confirmed we could derive solutions that achieve better results than the compared greedy methods. Our future work includes considering arrival of new patients. For this purpose, we may apply a policy to keep some amount of medical resources depending on the estimated number of potential patients.

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References

1. Higashino, T., Uchiyama, A., Yasumoto, K.: eTriage: A wireless communication service platform for advanced rescue operations. In: Proceedings of ACM Workshop on Internet of Things and Service Patforms (IoTSP) (2011) (Invited talk)
2. Gao, T., Pesto, C., Selavo, L., Chen, Y., Ko, J.G., Lim, J.H., Terzis, A., Watt, A., Jeng, J., Chen, B.R., Lorincz, K., Welsh, M.: Wireless medical sensor networks in emergency response: Implementation and pilot results. In: Proceedings of 2008 IEEE Conference on Technologies for Homeland Security, pp. 187–192 (2008)
3. Lenert, L.A., Palmer, D.A., Chan, T.C., Rao, R.: An intelligent 802.11 triage tag for medical response to disasters. In: Proceedings of American Medical Informatics Association 2005 Symposium, pp. 440–444 (2005)
4. Champion, H.R., Copes, W.S., Sacco, W.J.: The major trauma outcome study: Establishing national norms for trauma care. Journal of Trauma 30, 1356–1365 (1990)
5. Mizumoto, T., Sun, W., Yasumoto, K., Ito, M.: Transportation scheduling method for patients in mci using electronic triage tag. In: Proceedings of International Conference on eHealth, Telemedicine, and Social Medicine (eTELEMED), pp. 156–163 (2011)
6. Amani, D., Hayfa, Z., Slim, H., Herve, H.: A dynamic patient scheduling at the emergency department in hospitals. In: Proceedings of IEEE Workshop on Health Care Management (WHCM), pp. 1–6 (2010)
7. Emergo Train System, `http://www.emergotrain.com/`
8. Khoshnevis, B., Chen, Q.: Integration of Process Planning and Scheduling Funtcions. Journal of Intelligent Manufacturing 2(3), 165–176 (1991)
9. Weintraub, A.J., Cormier, D., Hodgson, T.J., King, R.E., Wilson, J., Zozom Jr., A.: Hybrid Genetic Algorithm and Simulated Annealing Approach for the Optimisation of Process Plans for Prismatic Parts. International Journal of Production Research 40(8), 1899–1922 (2002)
10. Guo, Y.W., Li, W.D., Mileham, A.R., Owen, G.W.: Optimisation of Integrated Process Planning and Scheduling Using a Particle Swarm Optimisation Approach. International Journal of Production Research 47(14), 3775–3796 (2009)
11. Xinyu, L., Chaoyong, Z., Liang, G., Weidong, L., Xinyu, S.: An agent-based approach for integrated process planning and scheduling. Expert Systems with Applications 37(2), 1256–1264 (2010)