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Pattern discovery from patient controlled analgesia demand behavior

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ABSTRACT

Unlike previous research on patient controlled analgesia, this study explores patient demand behavior over time. We apply clustering methods to disclose demand patterns among patients over the first 24 h of analgesic medication after surgery. We consider demographic, biomedical, and surgery-related data in statistical analyses to determine predictors for patient demand behavior, and use stepwise regression and Bayes risk analysis to evaluate the influence of demand pattern on analgesic requirements. We identify three demand patterns from 1655 patient controlled analgesia request log files. Statistical tests show correlations of gender ($p=.0022$), diastolic blood pressure ($p=.025$), surgery type ($p=.0028$), and surgical duration ($p<.0095$) with demand patterns. Stepwise regression and Bayes risk analysis show demand pattern plays the most important role in analgesic consumption prediction ($p=0.E+0$). This study suggests analgesia request patterns over time exist among patients, and clustering can disclose demand behavioral patterns.

1. Introduction

Pain is one of the most commonly reported postoperative symptoms [1]. It is a highly personal experience influenced by multiple factors, including sensitivity to pain, age, genetics, physical status, and psychological factors [2–4]. With the progress of medical science, people gradually became aware of the importance of pain management.

PCA (patient controlled analgesia) is a delivery system for pain medication that makes effective and flexible pain treatments possible by allowing patients to adjust the dosage of analgesics themselves within a preset range of therapy based on therapeutic and toxic effect. According to research [5,6], PCA is one of the most effective techniques for postoperative analgesia and is widely used in hospitals for the management of postoperative pain, especially for major surgeries. Most research on postoperative pain management is limited to evaluating the correlation of patient characteristics, such as demographic attributes, biomedical variables, and psychological states, with postoperative pain intensity or analgesic requirement. Several studies have identified the preoperative predictive factors for postoperative pain and analgesic consumption in various patient groups of different genders, ages, or psychological states [7–11]. However, none of these studies analyzed continual patient demand behavior throughout the PCA therapy. Time-series data analysis is a common practice in various research fields. For example, in the study of sleep in patients with insomnia, time-series data derived from sleep diaries were used to compute conditional probabilities of having insomnia [12]; in biology, a temporal map of fluctuations in mRNA expression of 112 genes during central nervous system development in rats provides a temporal gene expression fingerprint of spinal cord development [13]. Few studies of PCA examined patient demand behavior and its relationship to analgesic drug use [14,15]. We hypothesize that patient demand behavior over time provides different and useful information in PCA administration that is missing in the preoperative factors analyzed earlier.

Our study, unlike previous research, focuses on continual analgesia demand behavior during the postoperative PCA medication. The current study explores and characterizes patient demand behavior. Patient demand behavior is represented by a series of PCA requests over time. We discover distinct and conserved demand patterns from the time-series data and identify the significant patient factors that influence demand behavior. In addition, we compare the predictors for PCA demand behavior and analgesic requirements and evaluate the contribution of demand pattern to analgesic consumption prediction.

2. Materials and methods

2.1. Subjects and statistical tools

The study was conducted from 2005 to 2010 with the approval of Changhwa Christian Hospital (CCH) Institutional Review Board

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Table 1
Summary of patient attributes.

Attribute name	Description	Number	Mean ± sd
Demographic:			
Gender	Patient's gender	986(F)/669(M)	–
Age	Patient's age	–	56.9 ± 15.8
Weight(kg)	Patient's weight	–	63.0 ± 12.6
Biomedical:			
sbp (mmHG)	Systolic blood pressure	–	135.8 ± 22.6
dbp (mmHG)	Diastolic blood pressure	–	69.4 ± 13.8
Pulse(beats/min)	Heart rate	–	81.0 ± 15.4
ASA class*	1: Healthy 2: Mild systemic disease 3: Major systemic disease	184(1)/837(2)/634(3)	–
OP – related:			
op_type**	Surgery type: 1∼8	107(1)/126(2)/411(3) 127(4)/427(5)/109(6)212(7)/136(8)	–
ans_type	SA: spinal anesthesia GA: general anesthesia	1470(GA)/185(SA)	–
op_time(hr)	Surgical duration	–	4.2 ± 2.6
Urgency	E: emergency surgery R: regular surgery	136(E)/1519(R)	–

* ASA class is the commonly used preoperative index of physical status defined by American Society of Anesthesiologists.
** 1: intrathoracic, 2: upper intra-abdominal, 3: lower intra-abdominal, 4: laminectomy, 5: major joints, 6: limbs, 7: head & neck, 8: others.

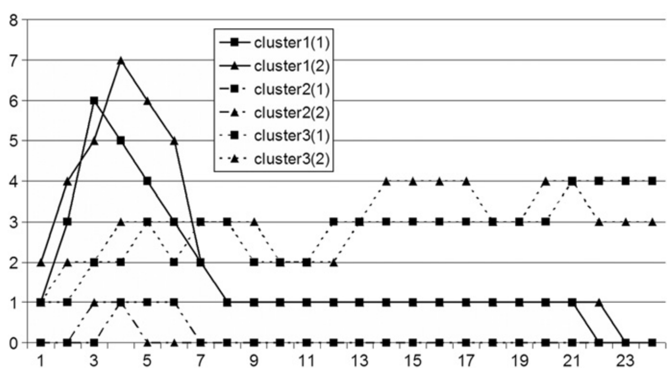

Fig. 1. An illustrative example of PCA demand patterns. Each curve represents the distribution of PCA demand frequency for a patient in 24 h. The *X*-axis indicates the 24 h time line (1 h to 24 h). The *Y*-axis represents the number of demand requests in a particular hour.

in Changhwa, Taiwan. Abbott Pain Management Provider (Abbott Lab Chicago, IL, USA) was used for patient controlled analgesia. Instructions were reviewed with patients before initiating PCA therapy. Each patient record contained attributes such as basic health status, age, gender, weight, department code, doctor ID, PCA control parameters, and amount of anesthetic used during different time intervals. Because not all the attributes are relevant to our study or have correct values, after consulting the anesthetists, we discarded irrelevant attributes such as doctor ID and department code before further investigation. We divide the attributes used in analysis into three categories: (a) patient demographic attributes, (b) biomedical attributes, and (c) operation-related attributes. Their values are either categorical or numeric. The attribute descriptions are shown in Table 1. All the statistical analyses were performed using the Statistical Package for the Social Science 10.0 (SPSS Inc. Chicago, IL, USA).

2.2. Analysis of PCA demand behavior

Given the PCA demand frequency within each unit of time, we can represent each patient's PCA demand profile as a time course, as illustrated in Fig. 1. The *X*-axis represents the 24 h time line, and the *Y*-axis indicates the number of PCA demand requests in a particular hour. By applying clustering algorithms to the time courses, we identified different patient groups. Patients in the same group are expected to demonstrate similar demand behavior; in contrast, demand behavior of patients in different groups is different. For example, Fig. 1 shows three patient groups, each consisting of two patients with similar demand patterns, and the demand patterns were different among different groups. In practice, we first transform the demand frequency into a sample standard score (i.e., z-score) to normalize the frequency variance in all units of time. This normalization step is to mitigate the influence of large variance on clustering. After normalization, each patient's PCA demand profile is represented by a vector of which each element is a normalized PCA demand frequency in a unit of time.

We use k-medoids algorithms [16,17] to partition the patients into clusters according to their demand behavior. In the current study, we use Euclidean distance to measure the similarity between two PCA demand profile vectors. A medoid is a real data point that has the minimum average distance from all other points in the same cluster. Unlike the k-means algorithm [18], k-medoids mitigates the effect of outliers on the resulting prototypes and ensures that all the resulting clusters are non-empty [19]. To find the appropriate number of clusters, we perform a series of k-medoids clustering algorithm with the value of k varying from 2 to K, a user-specified maximum number of clusters.

We generate bootstrap samples from the dataset by random sampling wit‘h replacement [20]. We run k-medoids on the sample to obtain a clustering solution. From B pairs of bootstrap samples from the original data, we produce B pairs of clustering results. Given two clustering solutions C_1 and C_2 from a pair of bootstrap samples, we obtain two partitions of the original data by assigning each observation to the nearest medoid. The number of clusters is determined by reproducibility and stability [21]. If the number of clusters is correct, it is more likely that k-medoids clustering of the bootstrap samples all converges to the real medoids, and reproduce the same partition of the original data. Even if not all clustering results converge to the same medoids, it is well anticipated that the converged medoids will be in the proximity of the real medoids of the clusters, and thus produce stable partitions. We use the adjusted Rand Index [22] to measure the similarity between the two partitions. To determine if the