Relations of time and effect of medical interventions

Dr. med. Michael Imhoff,
Surgical Department, Community Hospital Dortmund, D-44123 Dortmund, Germany
Dr. rer. nat. Roland Fried, Prof. Dr. rer. nat. Ursula Gather,
Department of Statistics, University of Dortmund, D-44221 Dortmund, Germany

Abstract

For the implementation of time-critical decision support algorithms a precise relation between intervention and effect needs to be established. We evaluated for catecholamines and infusions the relation in time between charted dose and effect on hemodynamic variables. The onset of the change of the hemodynamic variables was determined by autoregressive models. The lag of 13 min (0 - 29) between intervention and effect and the great variance of this lag pose an important problem for time-critical decision support. Even after optimizing data acquisition important factors remain unaccounted for. Therefore, decision support systems may need extensive testing with real-world data.

Introduction

Over the last couple of years knowledge-based systems have been developed that use CIS (Clinical Information System) data to support medical decision making[1]. Especially in operation-critical decision support such as in intensive care medicine a strong influence of the timing of interventions can be assumed. Therefore, in the implementation of time-critical decision support algorithms in a CIS a precise relation between medical intervention (time, dose) and effect needs to be established.

Methods

On a 16-bed surgical ICU all medication data was charted with a CIS at 1 minute time resolution. Online monitoring data was acquired from 148 consecutive critically ill patients in one minute intervals. Effects of interventions were defined as level changes in the time series of HR, MAP, and MPAP identified by second order autoregressive (AR) time series models[2]. For each estimation period of 60 min an AR model was fitted and applied to the prediction period of 30 min. The actual measurements were compared to the 95% confidence intervals (CI) for the prediction period. Values outside the CI were classified as a level change by 5 or more consecutive observations outside the CI. The time of the onset of a level change was defined by the first observation of this level change outside the CI. The time of the intervention was compared with the onset of the effect on the hemodynamic variables. An intervention was defined by a change in the dose rate of dobutamine, adrenaline, noradrenaline, nitroglycerin, or by a change of the fluid balance by more than 500 cc in less than 10 minutes.

Results

From a total of 80,752 time series analyses, 2.608 intervention-effect pairs met the inclusion criteria for further analysis. The average time difference between intervention as charted and detected hemodynamic effect was 13.23 minutes (0 - 29 min). This time lag did not differ significantly between catecholamines, vasodilators, and rapid infusions. The 90% percentiles for most intervention-effect combinations ranged from 0 to over 25 minutes. Changes of fluid balance showed an especially wide variation in their time lag to the associated effect.

Discussion

No study known to the authors addresses the issue of time-critical documentation in the ICU. This may be surprising as recent publications emphasize the significance of time-oriented data for clinical decision support[3]. It is pointed out that correct documentation of temporal patterns is essential for decision support in critical care[4]. The most striking finding remains the wide variation with a range of over 20 minutes for all interventions. This wide variation may be attributable to several user-related, pharmacological, and technical factors that may be beyond the user's influence. This time variance can significantly affect the performance of time-oriented decision support algorithms[3,4]. Some of the time variation may be reduced by improvements in data acquisition and processing: (a) Automatic data transfer from bedside devices wherever possible. (b) Training of users and standardization of charting procedures. (c) Optimization of algorithms for the detection of patterns and change points in time series data. (d) Adaptation of decision support algorithms to account for the variance in temporal patterns.

References

1. Morris A. Algorithm-based decision making. In: Tobin, MJ, editor: Principles and Practice of Intensive Care Monitoring. New York: McGraw-Hill; 1998. p 1355-81.
2. Imhoff M, Bauer M, Gather U, Löhlein D. Statistical pattern detection in univariate time series of intensive care on-line monitoring data. Intensive Care Med 1998;24: 1305-14.
3. Shahar Y, Combi C. Timing is everything. Time-oriented clinical information systems. West J Med 1998;168:105-13
4. Kahn MG, Marrs KA. Creating temporal abstractions in three clinical information systems. Proc. Annu. Symp. Comput. Appl. Med. Care 1995:392-6

Supported, in part, by the DFG (SFB475)