Empirical Study on Artifact Detection in Monitoring Data

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Abstract. *Artifacts in clinical monitoring are a serious problem, not just because they frustrate clinical staff, but also because they prevent computer researchers from easily exploring and exploiting the monitoring data. The best way of detecting artifacts still remains a controversial issue. In this paper, we present a simple and practical method for identifying monitoring artifacts. Experiments show that the method can detect most artifacts in 7 data sets of different preterm infants with very low birth weight.*

Keywords. Clinical monitoring, artifact detection, trend analysis

1. INTRODUCTION

Artifacts bedevil monitoring data and is arguably greatest in intensive care monitoring situations where the accuracy is probably most crucial. Deviation of data from expectation may be due to pathology, but statistically it is much more likely due to artifact [1].

Manual analysis and detection of artifacts could be a way of cleaning monitoring data, as done in [2]. However, it is generally not practically acceptable. Automatic detection depends on sophisticated prior knowledge of the problem under study [3], which may not be easily available. In this paper, we present a simple and practical regression method for detecting monitoring artifacts.

2. THE METHOD AND EXPERIMENT

From a given data stream that may or may not contain artifacts, we derive two new data streams, call the drop and rise streams. These two streams, as their names suggest, reflect the dropping and rising behaviors in the original stream, and are derived by comparing two successive data points in the original data stream.

For example, suppose that 176 176 176 172 176 175 173 69 142 170 170 169... is the beginning portion of the heart-rate data stream of an infant. The corresponding drop and rise streams are 0 0 4 0 1 2 104 0 0 0 1 and 0 0 0 4 0 0 0 73 38 0 1, respectively.

With a fixed time window, we can calculate the linear regression lines of the drop and rise streams. For example, if the time window is 7, -15.933+0.257t and –6.933+0.114t are the regression lines of the first six data points of the drop and rise streams, respectively. With the two regression lines, we predict that at the 8^{th} time point in the original data stream, there should be a drop by 2.32 and a rise by 1.18. However, the actual observation (i.e. 69) reflects a surprised drop from the previous one (i.e. 173). In fact, simple calculation shows that the observed drop is far beyond the 95% prediction interval of the predicted heart rate at time 8. So 69 is actually an artifact!

The story would be over if observations are always that simple. There are some situations where the linear regression lines may not be adequate. First, if the predicted drop (d) and rise (r) are both positive, then we are facing a contradiction. It seems that no simple resolution exists. We adopt a practical policy: If d>r, we believe that the next reading of heart rate should drop. Second, if d>r (r>d), and the observation actually represents a rise (drop), then we face another contradiction. In this case, we shift to non-linear regression, and fit a polynomial of 2 degrees into the original data portion, and use the polynomial to predict the real value of a parameter at the next time.

We have used 7 2-hour data sets of preterm infants to test the method outlined above. For data sets with no boundary artifacts (those whose are at the boundary of a series of artifacts), the true positive rates are 1, while the false negative rate is 0. But when boundary artifacts are presents in the other two test data sets, the true positive rate is only 0.75; however, the true negative rate is 1.

3. CONCLUSION

Through this work, we found that simple regression techniques may adequately identify artifacts in monitoring data. Although boundary artifacts are not easily to be identified by regression techniques, they may not be a serious problem, for we may remove some segment before or after a series of identified artifacts, as we are doing in our trend analysis research. (Supported by an HPKB ARPA grant).

References

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