Cooperative AI

in an

Unbalanced Distributed Environment

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1 Intelligent Health-Monitoring

1.1 Introduction

Although the main research on cooperative AI in an unbalanced distributed environment aims to be solution independent, sticking to a concrete real world model allows better modelling and evaluation of the research outcome. Thus, I will keep the application of an intelligent, mobile health monitoring system as a reference model for my research throughout the further work. This chapter should provide a good base knowledge about the issues related to health monitoring.. Be aware of the fact that building a better (more performant) algorithm for health monitoring tasks is definitely *not* a target of this research. The chosen health monitoring application just provides a good real-world example for building intelligence on restricted devices.

The main focus of the monitoring intelligence is to determine whether the patient is situated in a "normal" situation (every patient has a different definition of what is normal for him) or whether there is a situation of emergency. In the ideal case, the classifier could predict upcoming emergencies even before they are actually happening (data classification and data prediction).

To be able to classify alarm situations the health monitor has to process several inputs of physiological data (pulse, sweat, temperature, etc.) in relation to the current activity of the patient (sometimes mentioned as "context-awareness" in literature). It should be clear that physiological parameters identifying an alarm while the patient is sitting or sleeping do not automatically identify an alarm while the patient is running or carrying something heavy.

1.2 Physiological Input for Health-Monitoring

- what would be required at minimum to measure health condition?
- which parameters/sensors are available for monitoring? (portable, wearable sensors) e.g. Pulse, heart frequency, sweat, blood sugar, etc.
- discuss available sensors/sensor data with Eric; tightly relate to his project regarding available sensor data

1.3 Data Collection

[TSI00] found that training of classifiers results in more robust algorithms when training data contains more of the events of interest, i.e. in the ideal case the classifier is trained while a real event of health-emergency occurs. The problem is, that this research focuses on other kinds of events as Tsiens did, in fact it will be difficult to train the classifier with data while the patient actually having an emergency event. Tsiens research focused on the intensive care unit, where events are occurring on a regular timely basis.

1.3.1 Noisy Sensor Data

Noise in gathered sensor data (not optimally attached sensors, disturbing influences of environment, ...) influences the performance of the classification. It is hard to determine noise in sensor data, but the impact of noisy data can be reduced by integrating multiple sensor signals at once (also mentioned in [ZHA03]). Integration of multiple different sensor signals simply reduces the proportion of the noise related error within the whole input to the system.

As our proposed system focuses on monitoring several physiological sensors anyway, noise in sensor data can be treated with lower priority.

I would assume that to some extent the noise in sensor data is tightly related to the monitored individual: a sensor delivers noisy data because of physiological attributes of the patients, a patient (or his nurse) always attaches a sensor in the same way, the patient stays on places with disturbing environmental influences, ...). Therefore the adaptive monitoring intelligence should tackle this problem.

1.3.2 Characteristics of Learning on Sensor Data

In Machine Learning there are two kinds of data classification: One relates to classifying elements drawn from a population, the other to classifying sequences of data:

- iid = independently, identically drawn

versus

- sequential data

In the case of patient monitoring we clearly have sequential data classification, therefore classifiers have to perform time series prediction / time series analysis / sequence classification [DIT02].

1.3.3 Feature Selection

The input for the classifier algorithm has to represent a trend over a period of time somehow – classifying only the last measurement would only produce an isolated result for this moment. Classifying sequential data has to be a view on the development of the values (what was and what will be).

The extraction of a value representing a time-series of data is called “feature selection”, multiple features for multiple types of inputs are referred to as “feature vector”.

- Derive attributes for time-periods of input signals that represent a time-series of data, so called features. Combination of features for all input signals build a “feature vector”.
- Investigate different methods of how to tackle sequential data (how to derive/extract features from a sequence of measurements): sliding window, recurring sliding window, Markow models and related [DIT02]
- A short description of data abstraction ([RUS95]) - handled in more detail later...

1.4 Alarm Classes

Alarms raised by the intelligent health monitor can be categorised as adapted from [ZHA03], [TSI00]:

- TP-R: true positive, relevant
- TP-I: true positive, irrelevant
- FP: false positive (erroneous)
- or NO alarm (normal) state

The mobile monitor itself is not able to classify whether an alarm is clinical relevant or not, neither it is able to distinguish between true and false alarms. For simplicity, the mobile monitor has to identify whether the patient is in alarm or no-alarm state. Further classification and interpretation of the raised alarm has to be performed by subsequent systems (assistance node) and/or external examiners (for instance clinical staff).

- further description of what the classifications mean

1.5 Investigation of Classifiers

Many different approaches for machine learning algorithms have been developed within the last years. Many of them are per definition not applicable for monitoring a persons health, many others are. This research sustains on recent publications on health-monitoring related research and will refer to the most promising approaches. Some of them are well known in computer science:

- decision tree (DT)
- artificial neural network (ANN)
- support vector machine (SVM)
- genetic algorithms, genetic programming (GA, GP)
- etc.

The applicability of the classifiers for monitoring and/or predicting a patients health state has to be investigated, the classifier has to adapt to the individual patient (which could result into "imbalanced dataset problem").

Monitoring a persons "health" is a very general term in case of detecting abnormal physiological state. It has to be defined what abnormal patterns are of interest – e.g. regarding to the risk type a patient is belonging to.

1.5.1 Applicability of Classifiers

- Investigate and discuss performance of different learning approaches in the field of monitoring (ie ANN's perform better than classification trees, ANN's perform faster then GP, etc). --> mention performance test results of classifiers in [TSI00]. Just focus on the monitoring aspect here, not the machine learning aspects (these are treated in the next chapter(s)).
- check whether combination of inductive and analytical approaches like KBANN increase performance (see [MIT97] p. 334ff)
- Introduce findings of [ZHA03], [TSI00], [DOU04], ...
- Linear vs. Non-Linear Classifiers: a short comparison of linear and non-linear classifiers, which one are adequate for health-monitoring and why [PER03].

1.5.2 Performance Metrics

For evaluation of different machine learning approaches the definition of performance metrics for the classifiers is required (e.g. based on [ZHA03] and [PER03]: sensitivity, specificity, positive predicted value, accuracy). As this research doesn't aim to build a better classifier for (health) monitoring, this issue is to be neglected.

1.6 Individual Adaptation

Physiological classifiers clearly have to take the patients current "context" into account, physiological activities like sitting, sleeping, walking, eating, running, etc. are important criterias for sensor data interpretation. Additionally, even physiological measurements in a patients "idle state" (no activity) will be differing from person to person, the classifier has to learn the "normal" state in relation to activities (the context) of the patient.

1.7 Idea of "inverted training"

Training a classifier results in a more robust algorithm when the "events of interest" are occurring regularly within training data ([TSI00]) - when training the mobile node in our case, there is only little chance that events of interests (emergency) occur, in contrary to the ICU studies of Tsien and Zhang.

Idea to solve this problem:

- transform event of interest from the Alarm to the non-Alarm
- non-Alarm "events" are occurring regularly in our scenario
- train 2 classifiers: one where alarms are the "true"-labelled training examples, the other one where alarms are the "false"-labelled training examples.
- measure performance of both and identify the better approach

1.8 Further Issues

Not only in mobile telecare, health monitoring has to deal with several inherently related problems:

- measured physiological data has to be synchronized and combined with "external" (clinical) information, physiological measurements alone do not allow to classify the patients state correctly (see also [ZHA03])
- **parameter** values can be **missing** (e.g. a sensor failure, a cable detached, etc); missing

values have to be handled somehow

- **Simulation Database:** To allow efficient investigation and comparison of different machine learning approaches and classifiers a simulation database containing (virtual) physiological data of patients is needed.

  The **UCI Repository** provides a set of databases that are used by the machine learning community for the empirical analysis of machine learning algorithm:

  http://www.ics.uci.edu/~mlearn/MLRepository.html

2 Appendix

2.1 Notes

1.1 References

[TSI00] Tsien, C.L.TrendFinder: Automated Detection of Alarmable Trends2000

[ZHA03] Zhang, Ying; Real Time Analysis of Physiological Data a. Development of Alarm Algorithms i.t. Intensive Care Unit, M.I.T., 2003

[DIT02] Dietterich, T. G.; Machine Learning for Sequential Data: A Review, Caelli, T., 2002

[RUS95] Russ, T.A.; Use of data abstraction methods to simplify monitoring, , 1995

[DOU04] Dounias, G.; Linkens D.; Adaptive Systems and hybrid computational intelligence in medicine, , 2004

[PER03] Perlich, C.; Provost, F.; Simonoff, J. S.; Tree Induction vs. Logistic Regression: A learning curve analysis, William Cohen, 2003