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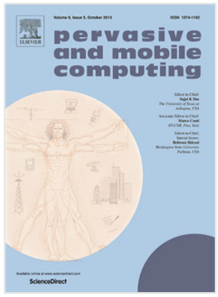

Unsupervised illness recognition via in-home monitoring by depth cameras

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Unsupervised Illness Recognition via In-home Monitoring by Depth Cameras

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Abstract

Most of today's in-home systems for detecting illness in the elderly meet with the same limitations: they target only single occupancy apartments, although couples may need support, too, and, faced with monitored subjects who are not necessarily regular in their everyday life, they tend to classify even slight deviations from standard routines (e.g. cooking a meal one hour later than usual) as anomalies. The training data used for anomaly detectors typically include only days when the subject is alone and not sick, whereas in practise it is difficult to obtain day labels, i.e. information on whether the elderly subject had visitors or felt well or unwell. In addition, as every room in the apartment to be monitored is usually equipped with passive infrared motion detectors, the maintaining of such systems may be inconvenient for the residents. To address these problems, this paper proposes a new probabilistic illness detector which does not rely on regular daily routines and requires no data labelling. The detector was tested in apartments inhabited by single elderly subjects or couples, and in all cases only the living rooms and corridors were monitored, with no invasion into the more private spaces. Despite its fully unsupervised training on data covering both normal and unusual days (days of illness, visits by other people, etc.), the proposed detector distinguished between normal days and illnesses with an average accuracy of 88% and did not misclassify the receptions of guests as anomalies.

Keywords: ambient assisted living, elderly monitoring, anomaly detection, depth sensor – based situation awareness, unsupervised learning

1. Introduction

Ambient assisted living (AAL) technology has recently become an active area of research due to the increasing numbers of elderly citizens: the human caregivers may not suffice in the future to support the elderly in living independent lives. In other words, there is a growing need for technological solutions that would relieve caregivers from having to make frequent personal checks of their elderly charges. Such systems should monitor their elderly subjects continuously and notify the caregivers of gradual health changes or detectable anomalies, e.g. illnesses, or wanderings on the part of dementia sufferers. The decision as to whether to send an alarm or not should depend on health of the subject and on the preferences of the subjects and their caregivers. Some caregivers may only receive alarms in cases of prominent anomalies, for example, whereas others may receive notifications in greater variety of cases, so that even if the caregivers were not very worried, they could make a phone call and express concern, as loneliness and emotional well-being are important issues in the care of the elderly [Acampora 2013, Greenhalgh 2014].

As anomalies are patterns in data that do not conform to expected behaviour [Chandola 2009], they can be detected by defining a region that represents normal behaviour and labelling any data sample that lies outside this region as an anomaly. "Normal behaviour" in humans can be very diverse, however, so that this approach would require learning separate models of normal behaviour in each monitored apartment. In any case, learning should not have to rely on the availability of labelled data, due to the difficulty of obtaining such labels. Even in assisted living facilities, professional caregivers do not provide "normal day" vs. "bad day" vs. "day with visitors" labels on a regular basis [Popescu 2012]. Obtaining such information from the monitored persons themselves is even more difficult, as they are not very eager to provide self-reports [Steen 2013], they may be difficult to reach by phone, and when reached, they may provide the wrong answers to questions regarding their bad days [Hein 2014]. To circumvent this problem, Hein et al. [Hein 2014] proposed that the monitoring system should be switched off when visitors come, but elderly people may easily forget to do this.

Nevertheless, existing monitoring systems often either employ supervised machine learning methods or need some other form of supervision in order to select perfectly normal behavioural data for algorithm training purposes (periods when neither visitors nor illnesses occurred). Shin, for example [Shin 2011], based anomaly detection on a Support Vector Data Description (SVDD) algorithm, which belongs to the family of unsupervised learning methods, but human supervision was still required for selecting the training data. This tendency to select only normal data for training purposes effectively rules out in-situ learning of behavioural models.

Another common trend in anomaly detection is to assume that human beings normally have regular routines, while irregularities are abnormal [Candas 2014, Lotfi 2012, Ordonez 2015, Shin 2011, Steen 2013]. This approach has proved helpful in the case of certain types of illness. For example, irregular motion patterns of a woman diagnosed with Parkinson's disease indicated her sleeping problems and allowed to conclude that her new medication did not help [Ordonez 2015]. Monitoring activity levels at night can also reveal anxiety [Noury 2011], but in general terms routine-based anomaly detection is too rigid: it does not work well when the monitored subjects do not have strict routines [Lotfi 2012, Candas 2014], and it tends to classify as anomalies many very ordinary deviations from routines, such as cooking a meal an hour later than usual [Steen 2013], waking up later than usual [Candas 2014, Shin 2011], cleaning the bathroom [Steen 2013] or cleaning the house at unusual times [Shin 2011].

We therefore set out here to present an in-home monitoring system that does not require data labelling and does not rely on regularities in daily routines. This system monitors only the most public apartment areas (the living room and a