Hijacked Smart Devices
Methodical Foundations for Autonomous Theft Awareness based on Activity Recognition and Novelty Detection

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Abstract: Personal devices such as smart phones are increasingly utilised in everyday life. Frequently, Activity Recognition is performed on these devices to estimate the current user status and trigger automated actions according to the user's needs. In this article, we focus on improving the self-awareness of such systems in terms of detecting theft: We equip devices with the capabilities to model their own user and to, e.g., alarm the legal user if an unexpected other person is carrying the device. We gathered 24hours of data in a case study with 14 persons using a Nokia N97 and trained an activity recognition system. Based on it, we developed and investigated an autonomous novelty detection system that continuously checks if the observed user behavior corresponds to the initial model, and that gives an alarm if not. Our evaluations show that the presented method is highly successful with a successful theft detection rate of over 85% for the trained set of persons. Comparison experiments with state of the art techniques support the strong practicality of our approach.

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1 INTRODUCTION

More and more smart devices are available nowadays, interconnected and always trying to improve our daily lives. Their automated support ranges from reminders for meetings via navigational assistance to analyzing and improving our running style. Their ubiquitous assistance is completely pervading our personal environments. It is also common that users have more than one smart device, as old ones are rarely disposed or sold. Unfortunatly, the monetary value of such devices is also very high, so that thefts are quite common, especially in urban areas. Even though it is possible to track a stolen device afterwards, an active involvment of the user in particular is necessary – and often happens when it is already too late. The major challenge with such approaches is that theft and the discovery of the theft might be hours apart. So instead, we envision an approach, where the device itself recognizes whether it was stolen or not, autonomously, based on internal sensors. Such self-aware systems can then trigger counteractions or alarms timely, even before the legitimate user misses the device. In terms of developing such self-* properties, the proposed approach augments the concept of initiatives such as Autonomic Computing (Kephart and Chess, 2003) or Organic Computing (Tomforde et al., 2017). In particular, we aim at providing capabilities to autonomously observe the user behaviour and estimate whether the device itself is still carried by the owner or not. In case a severe deviation of expected behaviour is noticed, the owner can be notified immediately on a backup-channel or sensible information can be secured even stronger.

Our proposal uses methods from the field of Activity Recognition (AR) to model the characteristics of users activities. Methods from the field of Novelty Detection (ND) are then used to detect, whether a carrier's activities still match that model or deviate from the expected behavior. So far, such a combination of approaches from these different research directions does not exist. We see our approach as an important part towards creating self-awareness in technical systems, as the detection of environmental changes is integral to such a task.

In this article, we use a probabilistic, generative approach based on Gaussian Mixture Models (GMMs) to classify daily activities from smartphone data. The evaluation of our method involves a case study with activity data from 14 users and 5 sessions of approx. 20 minutes each, so the overall database comprises of roughly 24h of user data. Even though

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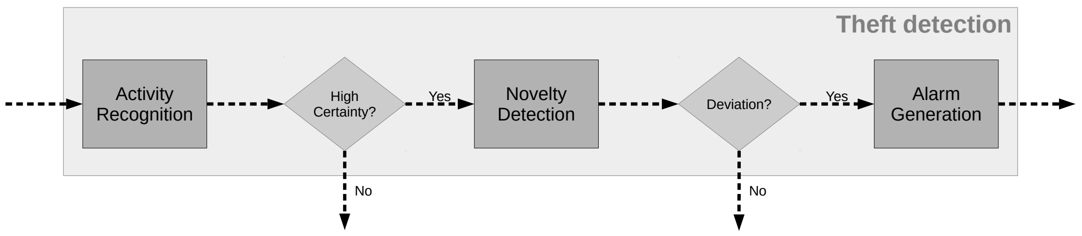


Figure 1: System parts involved in a theft detection that can run on smart devices. With input being processed by the AR component (see Section 3 for details), output with high certainty is forwarded to a ND component (see Section 4 for details). If a deviation to a pre-learned model is measured, an alarm can be generated and further actions taken.

the data uses very basic daily activities, our approach is not limited to them. The used GMM captures structure in arbitrary data, so it is not confined to a predefined set of activities. Based on the trained models, the detection of novel data is investigated and discussed in depth. By detecting novel / previously unknown data, it is possible to realize an autonomous theft detection that works quite well, even with data from very simple activities. Figure 1 gives an idea, how such a system can be designed.

The **key contributions** of our work are **1.** the introduction of methods to realize an unobtrusive security feature for body-worn smart devices and **2.** to realize a theft detection with a very simple and common sensor, along with easy to compute features of very basic, daily activities.

The remainder of this article is structured as follows: In Section 2 our approach is put into perspective with the work from other groups in the area of ND. In Section 3, the solution for the AR task based on acceleration data is presented. Based on optimized AR-models, our approach towards the problem of novelty detection is addressed in Section 4. Afterwards, in Section 5, a realization of a smart device with theft detection capabilities is sketched. This work is then concluded by a summary in Section 6, discussing the evaluations and giving an outlook on further work.

2 RELATED WORK

Our related work briefly touches the field of Activity Recognition (AR), but mostly focuses on Novelty Detection (ND). The term AR was first publicly discussed nearly 20 years ago by Abowd et al. (Abowd et al., 1999) and has since then gained a lot of popularity among researchers. The greatest challenge of inferring a user's activity from body-worn devices was pursued since day one (c.f., e.g., (Clarkson et al., 2000; Gellersen et al., 2002)). A first step moved research from visual data (i.e. probands were filmed) to movement data from body worn sensors. Those sensors were packed in sensor-nodes and strapped to the body, on arms, torso, thighs, etc. Later, smartphones became more popular in research, due to the sensors of interest being integrated and their increasing computing power. Those two properties led to Machine Learning (ML)-techniques being implemented on the devices, so that the recognition could happen effortlessly.

Addressing preparations for ML algorithms, Lau et al. (Lau et al., 2010) focused on various parameters that have an influence on feature computation. They investigated different sensor sampling frequencies (8, 16 and 32Hz) along with different sliding window sizes (0.5s, 1s, 2s, 4s) and different sliding window overlaps (25%, 50%, 75%), with features being calculated from each sliding window. The results revealed that a sampling frequency of 32Hz, a sliding window size of 4 seconds (128 measurements) and an overlap of 75% achieved the most accurate results for recognizing daily activities. Besides that, similar activities (like Walking, Ascending stairs and Descending stairs) were often mixed up by the classifiers under investigation. The work of Franke et al. was also focused on technical details and preprocessing in recognizing daily activities (Franke et al., 2009). They put a lot of effort into recognizing user activities based on sound samples of a smartphones microphone, that itself was carried in different pockets. However, they did not investigate advanced ML-techniques in depth.

The question of how to model recorded data is following: *Which modelling technique(s) should be used to represent the data?* In (Chen et al., 2012) the authors give an overview of different methods, as well as approaches based on prior problem knowledge (so called “Knowledge driven”). An explicit distinction between discriminative approaches (e.g. Support Vector Machines (SVMs)) and generative approaches (e.g. Hidden Markov Models) is made and discussed in depth. Despite their discussion of different approaches that were tried for AR scenarios, the authors neglect the heavy influence of chosen training algorithms. Our experience showed, that a paradigm can perform somewhere between excellent and very bad, only depending on the training algorithm; sometimes even only the initialization of the very same training algorithm. The authors also mentioned, that they did not discuss inconsistencies and missing values in training data, but both effects commonly appear in real life datasets. Even though classifiers of various kinds are investigated, in practical applications, most common solutions prefer discriminative techniques, completely neglecting the information that can be extracted when using generative models (e.g. structural information of training data). While often superior in terms of classification performance, no further information other than the class prediction can be extracted from discriminative models. Contrarily, generative models approximate the structure of the data and thus allow the detection of datapoints that do not fit that structure: outliers. With this huge advantage, we decided to use a generative representation over a discriminative one.

Outlier detection or Novelty Detection (ND) focuses on the detection of data, that does not fit a specific data-model. With a trained model at hand, observed data is expected to fit that model, because an implicit assumption usually is, that training data is representative and thus the model trained on it is a good representation of expected data to come. However, over time, or due to changes in the observed environment, the distribution of observed data may change and that assumption is violated. Suppose an input space with several clusters and, at some point in time, a new cluster arising, which is not covered by the data-model. Those datapoints can be seen as outliers with respect to the model or, as *novel*, if never before observations were made in that region. A first categorization of ND approaches was done by Markou et al. and depicted two groups of detection mechanisms. One group included statistical methods, relying on trained models (Markou and Singh, 2003a). Datapoints were depicted as novel, if they differed too much from that model. According to the authors, statistical approaches involved non-parametric models (e.g., k nearest neighbor approaches or density estimators), as well as parametric models, for which certain assumptions on the data distribution are made. The second group was associated with neural network based approaches (Markou and Singh, 2003b), however, should not be discussed further, as our method clearly is a group one approach. The authors put a common technique in the second group, namely the detection of outliers via One-class SVMs, but to our understanding the approach is not neural network based. The approach was first suggested by (Schölkopf et al., 1999) and later applied to the problem of object recognition based on image data by (Tax and Duin, 2002). The authors used an artificial dataset with artificially added outliers, as well as images from handwritten digits with artificially added outliers. Even though a certain feasibility was shown, the authors had no real life dataset to proof their concept. Apart from that, the approach was accepted for outlier detection among researchers and later applied to, e.g., intrusion detection scenarios ((Li et al., 2003)) or the detection of abnormal nodes in wireless sensor networks ((Zhang et al., 2009)). In both cases, training data representing a *normal* situation were used to train One-class SVMs and the goal was to detect deviations from it.

The novelty detection mechanism we propose is based on a Gaussian Mixture Model (GMM) and uses a state variable to define the current status of data fitting the model. The parameters associated with the measure then enable users to influence the tradeoff between detection-accuracy and time-to-detection. The technique was introduced and first used by Fisch et al. in (Fisch et al., 2009).

Related Work in a Nutshell: As noted at the beginning of this section, Activity Recognition based on body worn sensors, like smartphones, smart watches or other wearables, is the current way to go in research. Even though preprocessing steps have heavily been researched, detection algorithms mostly ignore usable information available in the dataset. So, with respect to information gained from datasets, there is room for improvement. Secondly, the field of novelty detection has a broad field of techniques at hand, however, only few were investigated on real life datasets.

To address the first point, we see big potential in the use of probabilistic, generative approaches and thus investigated the usage of classifiers based on Gaussian Mixture Models and present results in Section 3. Building on top of that, we are first in the field of theft detection based on such models and discuss our proposal in depth in Section 4.

3 ACTIVITY RECOGNITION

In Section 1 the overall approach with all necessary steps for a theft detection (Activity Recognition (AR), followed by Novelty Detection (ND)) were introduced (c.f. Figure 1). In the following section, all experiments that were performed to reach a most accurate activity prediction are discussed.

The used dataset was recorded at our institute and comprises of the data of 14 different users. Each user followed a script that described which activity should be performed how long and in which order. Each run of the script was repeated five times, with a maximum of two sessions on the same day, to reduce self-similarities in the data. The activites under investigation were *Walking*, *Ascending Stairs*, *Descending Stairs*, *Standing* and *Sitting*. Please note that, while these activities are very basic, our techniques are not confined to them and, as will be explained, GMM are rather powerful modelling approaches that can capture all kinds of data. The five basic activities are chosen exemplatory, for comparison with other studies (cf., e.g., (Kwapisz et al., 2011; Lau and David, 2010)). All data were three-dimensional acceleration data recorded on Nokia N97 with a highest possible frequency of 182Hz. Overall 70 sessions with an overall length of approximately 1400min were recorded and labeled.

Preprocessing steps included a resampling to 32Hz (cf. Section 2), a linear interpolation of missing values, a feature extraction and a standardization. On our path to train an optimal classifier, we quantified the influence of 1. an additional sensor dimension, 2. different features, 3. optimized parameters and 4. aggregated classifier outputs.

The first step towards improving AR performance was the addition of the *magnitude* as additional value. The values of this new "dimension" were calculated as the length of the acceleration vector by using the Euclidean distance:

$$mag = \sqrt{x^2 + y^2 + z^2}. \tag{1}$$

Afterwards, for every dimension the following four features were extracted:

- mean
$$\mu = \frac{1}{N} \sum_{n=1}^{N} x_n, \tag{2}$$
- standard deviation
$$\sigma = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} (x_n - \mu)^2}, \tag{3}$$
- energy of Fourier transformation
$$energy = \sum_{n=1}^{N} fft_n, \tag{4}$$
- information entropy of Fourier transformation
$$entropy = \frac{-1}{\log(N)} \sum_{n=1}^{N} fft_n \cdot \log(fft_n), \tag{5}$$

with fft_n being the magnitude of the n-th Fourier coefficient.

All features are extracted by a sliding window approach (which is quite common in AR, cf., e.g., (Lau et al., 2010; Sun et al., 2010)) with a size of 128 values and an offset of 32 (followingly 75% overlap); aggregating 4 seconds of data, for one classification prediction each second.

The generative approach we used as a classifier is also used as a basis for the novelty detection mechanism later (see Section 4), as the detailed modeling of data enables a well working outlier detection. Generative approaches model the given data by means of a density model; so that after training, data generated by this model would underly the same distribution as the original training data. We focus on a Classifier based on Gaussian Mixture Models (CMM), trained by a realization of Variational Bayesian Inference (VI), a method proposed in (Bishop, 2006a).

The second optimization step was a better computation of features to allow a better discrimination between *Ascending stairs*, *Descending stairs* and *Walking*. As it turned out, the most vivid combination was the replacement of the Fourier coefficient based features by a high-pass-filtered version, where mean and standard deviation of that coefficients are used. The great performance of this replacements is no coincidence, but was previously observed by others (cf. (Junker et al., 2008)), stating that "simple" features (mean and standard deviation) perform very well most of the time.

The next step was the optimization of classifier parameters. A popular method from the domain of ML is a parameter grid search, so that an optimal configuration for the classifier can be used in a practical application. However, a detailed grid search is exhaustive, since it tests every possible parameter combination. It also comes at very high computational costs, with respect to time and resources. We used four out of five sessions for the parameter search, while keeping one session to use as test data for the evaluation. The parameter optimization was also carried out in a five-fold cross-validation, with four parts being used for training and the fifth part being used for parameter-validation. This leads us to have 70 (14 users, 5 sessions each) different models, each one with the need for a grid search on three of the four VI-parameters (cf. (Bishop, 2006a)). To find optimized parameters for CMM we use an initialization heuristic with initial centers being placed farthest apart from each other as described by Bishop (Bishop, 2006b), with an initial number of 50 components. Convergence criterion for the training algorithm was a Likelihood function, with a convergence threshold of 0.01 between two consecutive steps. The parameter α was varied between 0.1 – 0.5, β between 0.1 – 1.0 and w between 0.01 – 1.0 (names of apramenters as given by (Bishop, 2006b)). As known from comparable scenarios, these regions are most interesting. Every possible combination of the points is evaluated by a five-fold cross-validation (overall 17920 classifier trainings), with the classification error of the validation data being the comparison measure and the lowest error denoting the best fitting model.

As a last step to improve the classification performance, a short term memory is added right after the classifier. This is motivated by the fact that users are unlikely to change their current activity for just a short period of time. E.g. with our preprocessing, every second a class prediction is made; but *Walking*, *Sitting*, *Walking* is a highly implausible chain of activities. The size of this memory, which was realized as a FIFO buffer, had varying sizes between 2 and 10, storing the last activity predictions. The classifier as we used it before, is not affected in any way. The final system prediction is determined by a simple majority vote on the buffer. If there is no majority, the last majority decided value will be taken and if the buffer is not filled yet, the classifier output will be as usual. Please note that whith each real activity transition, there is a delay in system output. However, numbers clearly indicate that those few misclassifications (which only occur on activity transitions) compensate the greater number of (otherwise misclassified) "outliers" during normal operation.

Buffer sizes 2, 3 and 5 are favorable, depending on whether recognition speed is important to an application or not. In our case, a buffer size of 5 implies a prediction delay of 3 seconds between activities.

Taking all optimizations into accout on a per-user-basis, the overall improvement based on five-fold cross-validations, leads to an average classification error of 6.99% ± 2.79%, which is an error reduction of 7.63%. It is also worth mentioning, that wisely chosen features lead to the greatest improvement (3.55%), whereas a parameter optimization of the training algorithm reveals a surprisingly low improvement (0.17%). This results are summarized in Table 1.

Table 1: Classification errors of test data with one additional optimization added in each step, showing one step per line. The last line represents the setting with all optimizations active. Mean ± Standard Deviation are evaluated by five-fold cross-validations and aggregated across all 14 users. The best results are shaded gray.

Dimensions	**CMM** $E_{Te}[\%]$
baseline	14.62 ± 5.00
+ additional dimension	12.52 ± 5.06
+ better features	8.97 ± 3.20
+ grid search	8.80 ± 3.26
+ short term memory	6.99 ± 2.79

4 NOVELTY DETECTION

The Novelty Detection mechanism of choice is described in this section, along with the performed parameter optimization and experiments. The measure is based on CMMs and was first proposed by Fisch et al. in (Fisch et al., 2009). It is bound to [0.0, 1.0] and based on a penalty/rewards scheme, i.e., with each new observation a variable is either increased (datapoint fits the model) or decreased (datapoint seems to be an outlier). The term novelty stems from the first applications of this measure, where data (that is unknown to a generative model, cf. Section 2) represented novel processes in the input space. Followingly, a "dissatisfaction" of the measure with the current model was the result: There were more penalties than rewards for the observations and thus the measure fell, eventually below a predefined threshold. Please note that the detection mechanism can be applied to GMMs of any kind. Here, the pretrained models from Section 3, that are based on basic daily activities, are used for all evaluations.

4.1 Parameter Optimization

The novelty detection mechanism has two parameters (α, η) and once the measure falls below a given threshold, it indicates a difference between observations and data-model. The parameter α describes the fraction of datapoints that should be seen as "normal" with respect to the model, with 1 - α denoting the fraction of outliers that is acceptable. Values from the interval [0.75, 0.95] were chosen in 0.05 steps. Other values were not investigated, as data with more than 25% outliers (α = 0.75) or less than 5% outliers (α = 0.95) might appear in data – but to our understanding, would only be so extreme due to bad models. The parameter η describes a kind of sensitivity, i.e., the magnitude of the measure's punishment and reward factors. As in comparable datasets, tested values were chosen from the interval [0.001, 0.1] in 100 equidistant steps. Finally, the threshold γ allows for statements about data-to-model fitment: If the measure stays above that threshold for every datapoint (more reward than punishment), the current data and the training data seem to underly the same distribution. Hence, the model covers the data well and the novelty measure stays up. In contrast, data that underly a different distribution than the training data, will reduce the novelty value until it falls below γ. It is obvious that η and γ are connected: a lower threshold can be reached within the same number of datapoints as a higher one, if the sensitivity is increased. Furthermore, the adaption of one parameter can be compensated by changing the value of the other parameter, resulting in the same effects. Due to this, γ was fixed before η was adjusted independently for each user.

In our experiments, the goal is to find an η for each investigated α, so that no novelty is detected for the own user, but for all other users, as fast as possible. For γ, 8 equidistant values from the interval [0.0, 0.7] were investigated. If more than one η fulfilling the condition during validation was found, it was averaged for final testing. For a detailed description of the parameters please refer to (Fisch et al., 2009). For all evaluation scenarios two graphs were generated. The figures for success rates show the reached values, illustrated by a bar for each α and γ combination for a fitting η, which was determined by the respective method. The success rate is composed of user data (bottom), where no novelty should be detected and data from other users (top), for which the measure should fall below γ for success.

Because there is more data from other users than from the actual user (Ratio 13 to 1), the results are weighted accordingly to have a maximum af 50% each, so that the overall maximum is 100%. The average time needed for a novelty detection is displayed by a line chart. This time is only determined by the number of successfully detected novelties. Displayed values of both graphs are averaged results of five-fold cross-validations from each user.

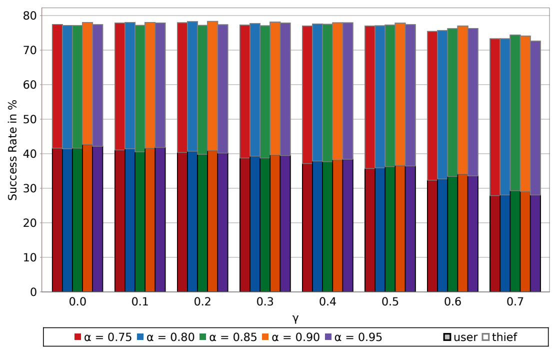
When looking at working combinations of α and γ, successful detections mean that a fitting η was found during our experiments.

One way to configure the η parameter for each user, would be the usage of the training data to optimize the parameters. In other words, the optimization takes place with data, which "is known" to the models. However, a major concern for this scenario is overfitting: If the data was used to create the model, how representative would an optimization on its basis be?

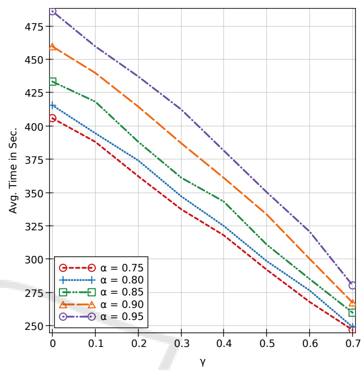
As we wanted to use unknown, but user-fitting data to find a specific η, additional validation data was necessary. To address this issue, models were trained with only three out of five user-sessions, with one of the remaining sessions being a parameter validation set and the other one being the parameter test set (**V-VAL**).

The model parameters themselves were optimized via grid search on α and η.

The optimization was aiming at an η, that made the novelty measure sensitive enough to reach a value in the interval [0.74, 0.76] for the correct user at least once, however, the measure was not allowed to fall below that interval. This specific interval can also be interpreted as follows: The target was to adjust the



(a)



(b)

Figure 2: Success rates (a) and average times (b) of a novelty detection with various configurations of the novelty measure (**V-VAL**). For further description please refer to Section 4.1.

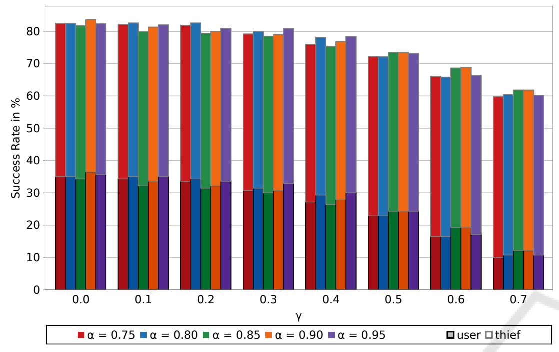
sensitivity, so that a 25% deviance on the current user's validation data was allowed with a tolerance of 1% (0.75 ± 0.01). With that condition satisfied, all other test-users should be detected by the so parametrized measure.

Figure 2 visualizes the evaluation: The higher the demanded recognition threshold γ, the lower is the rate of successfully detected novelties. Everything considered, this means that for a predefined threshold (γ) the chance of finding a suitable sensitivity (η) decreases when the fraction of tolerated outliers is reduced (α is risen).

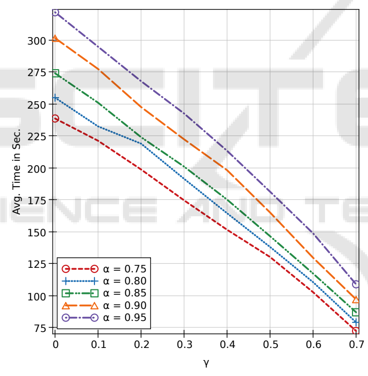
It can also be seen that for different γ the success rate hardly differs; basically proving the dependence between γ and η: for nearly every threshold, a sensitivity can be found. A first significant drop of the success rate can be recognized for a γ of 0.60. The best average detection time was reached for α-values of 0.75 and 0.80.

4.2 Ensemble-based Approach

As three out of four training datasets are used to train the model on which novelty parameters are validated with the fourth session, four different models can also be stored and used as an ensemble for novelty detection. With several models, a number of ensemble members have to agree on the type of a datapoint (outlier or model-compatible), before the dataset under investigation can be identified as fraud.



(a)



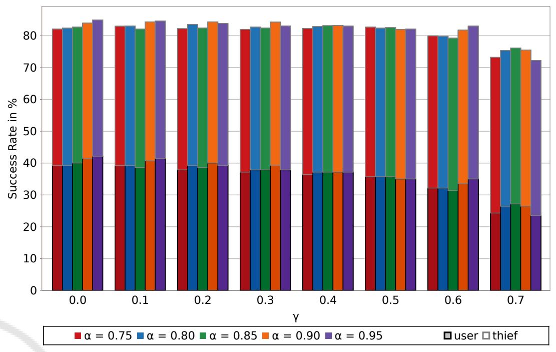
(b)

Figure 3: Success rate (a) and average detection time (b) of novelty detections based on **ENS** with a majority of 1 out of 4 members (ENS_1). For further details please refer to Section 4.2.

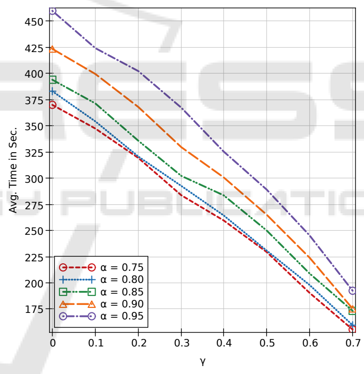
Four novelty detections were run in parallel for one test session. Deviating data is detected, as soon as a predefined majority of the ensemble detects a novelty (**ENS**).

In Figures 3 to 6 the evaluation results are visualized. A majority of one (Figures 3a and 3b) results in a rather sensitive ensemble, that seems to be overcautious, the higher the detection threshold is selected. This means that novelty is easily detected, but also that the rightious user is more often falsely detected as non fitting the data. This can be seen in the success rate for data from other users, which is nearly at the maximum of 50% for each α. However, in turn the success rate on legitimate user data is way below 50%; with $\gamma = 0.70$ even around 10% for each α. A γ of 0.20 seems to be a practical value, because the success rate on the user's data starts to drop from 0.30 onwards. With this low γ, an α of 0.80 reveals the best success rate and the second best detection time.

For each threshold, a majority of two increases the detection performance (Figures 4a and 4b). A γ of 0.60 and an α of 0.95 are a good choice here, as the success rate is high and the detection time fast.



(a)



(b)

Figure 4: Success rate (c) and average detection time (d) of novelty detections based on **ENS** with a majority of 2 out of 4 members (ENS_2).

For a majority of three (Figures 5a and 5b), the success rate for novelty detection is slightly rising with an increased γ, while the false alarm rate also increases (user success rate decreases). In order to keep the detection time low, a γ of 0.7 and an α of 0.75 seem to be a good choice.

The majority of four is yet another special case (Figures 6a and 6b). The insensitivity against deviating data is rather high and takes comparatively long, even with high thresholds (e.g. $\gamma = 0.60$ or 0.70). Output from this model can be interpreted as very reliable, however, successful detections take a very long time. A γ of 0.70 is the only meaningful value here.

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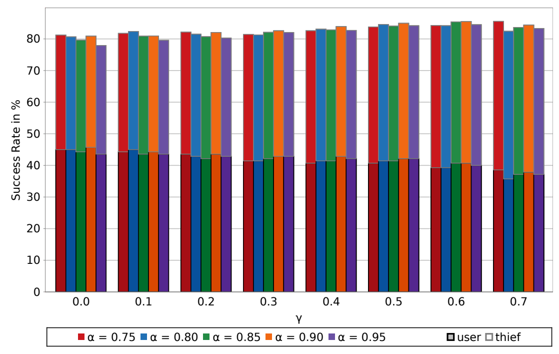
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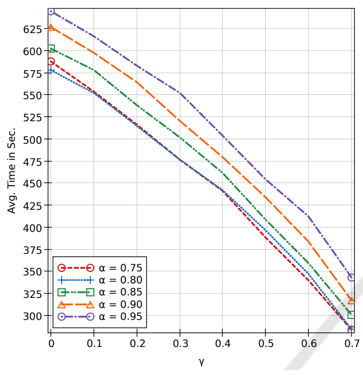
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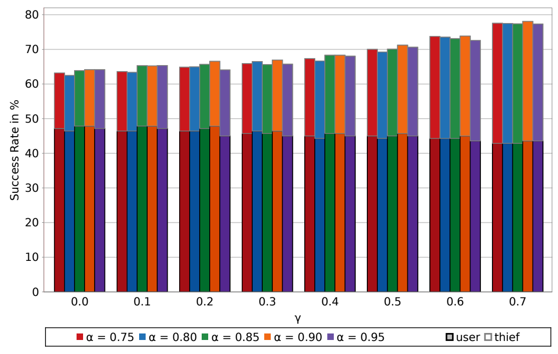
Figure 5: Success rate (e) and average detection time (f) of novelty detections based on **ENS** with a majority of 3 out of 4 members (ENS_3).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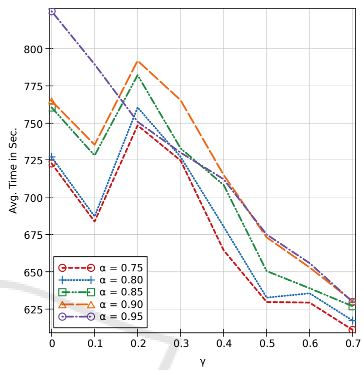
(b)

Figure 6: Success rate (g) and average detection time (h) of novelty detections based on **ENS** with a majority of 4 out of 4 members (ENS_4).

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Due to the lowest detection time with such an ensemble, an α of 0.75 would be an appropriate choice.

4.3 One-class SVM

For a comparison we decided to focus on One-Class SVMs, which are commonly used for outlier/anomaly detection ((Fernndez-Francos et al., 2013; Amer et al., 2013; Guerbai et al., 2015)). Positive data (in our case data from the actual user) is often used to train a discriminative function, which then outputs whether data belongs to the positive class ("+") or not ("-"). For that purpose, ν-SVMs with a Radial Basis Function (RBF)-kernel ($\gamma_{RBF} = 0.10$) were trained in the same manner as before, i.e., three out of five sessions were used for training, a parameter-optimization was done on a fourth session (validation session) and the evaluation was done with the remaining session (test session). For the optimization step, the overall number of positive outputs from the validation set was used: The more positive predictions a certain parameter value caused, the better the trained SVM (and thus the current ν) was considered.

As ν can be interpreted as a maximum accepted fraction of datapoints outside the region of interest, it is comparable to the parameter α from our novelty measure and thus, values $\{.05, .10, .15, .20, .25, .30\}$ were investigated. Cross-validated over all users, $\nu = 0.05$ turned out to be the best available parameter, i.e., the maximum number of accepted datapoints was reached for that parameter.

The next challenge on ν-SVMs is the creation of a mechanism for novelty detection, so that outliers are recognized with a specific certainty: Our method of choice was the short term memory technique as introduced for the AR-task in Section 3. The necessary majority for outliers within a window was fixed to being greater than 50%. For each user, a specific window length was found. Starting with a window length of 3, the size was incremented up to the point, where all other users where recognized as being different (had more outliers in the sliding window than accepted datapoints), which corresponds to the fastest possible reaction time in terms of novelty detection. Given an optimal sliding window length, the following criteria had to be met for a working configuration: 1. the dataset of the current user has to cause less than

50% outlier predictions, while 2. for each other user, the fraction of outlier predictions was greater than 50%.

Still, as a result, only 328 out of 930 (14 users with 13 datasets from other users and 5 sessions of each other user being tested) novelties were actually detected. Results are summarized in Table 2.

Table 2: Comparison of the success rates and average detection times of all users using parameter optimized ν-SVMs. Average values in the shaded line are given in the form mean ± standard deviation.

User	***Success Rate*** [%]			***Avg. Time***
	user	non-owner	total	[s]
1	80.00	13.85	46.93	1182
2	100.00	38.46	69.23	1262
3	80.00	60.00	70.00	1117
4	80.00	27.69	53.85	1114
5	60.00	27.69	43.85	1198
6	100.00	33.85	66.93	1075
7	80.00	80.00	80.00	858
8	80.00	33.85	56.93	1018
9	80.00	40.00	60.00	1109
10	80.00	27.69	53.85	901
11	100.00	16.92	58.46	1322
12	100.00	4.62	52.31	1032
13	80.00	3.08	41.54	1212
14	80.00	96.92	88.46	442
∅	84.29 ± 11.58	36.04 ± 26.87	60.17 ± 13.48	1060 ± 204

From the table can clearly be seen that the acceptance of user data by the trained ν-SVM is rather high, however, the detection rate of non-owner-data is very bad: Out of 65 possible detections (13 other users, 5 sessions each) at most 62 (in the case of user 14th SVM) and at least 2 (in the case of user 13th SVM) were detected as not-fitting. Furthermore, the average detection time is quite high. Overall can be stated, that a One-Class SVM seems unsuitable for novelty detection tasks in AR-scenarios. This statement is supported by the fact, that the average detection accuracies have a very high standard deviation.

4.4 Discussion

In Table 3 a comparison of our new techniques along the commonly accepted One-class SVM approach is visualized.

Parameters α and η for our novelty detection approach were optimized by means of a grid search. In the SVM-case, ν was chosen by detection accuracy, with the radius of the kernel functions γ_{RBF} fixed to 0.10 and the majority of the necessary sliding window content fixed at 50%. Whereas the SVM struggles most with an overall working detection, our approach is working and can even be parametrized to the user's needs: The tradeoff between accuracy and detection speed is the biggest issue and should be handled with care, depending on, e.g., whether false alarms are acceptable or not. In all investigated scenarios, the SVM delivers a mostly bad performance for novelty detection, while offering a rather acceptable performance for identifying the correct user. The influence of novel data however, leads to a seemingly random behaviour. Furthermore, the SVM-based approach is completely inappropriate in terms of fast detections.

When false alarms (the actual users data is detected as foreign) should be avoided at all costs, an ensemble with a majority of 4 out of 4 (ENS_4) seems to be the method of choice. It has the highest success rate (85.71%) for correctly identifying the owner, however, this comes 1. at the cost of the lowest detection rate for non-owner-data and 2. also a long detection time of more than 10 minutes (611 seconds). It should also be noted that GMM-based approaches allow for a more precise statement, be it on user- or non-user-data. This seems to be a manifestation of the generative property those models possess.

If a good trade-off between success rates for user and novelty detection is targeted, an ensemble with a majority with 3 (ENS_3) is the best choice, with the highest total success rate of 85.55% and a rather acceptable detection time of 284 seconds in average.

5 THEFT DETECTION

To train an autonomic theft detection for smart devices, it is necessary to train user models, that are as specific as possible.In terms of high quality data-descriptions, estimations via GMMs are very suitable. AR-datasets as used in this study of feasibility can be collected explicitly or implicitly while a user follows his regular routine. With the goal of detecting unknown data (e.g., data from non-owners), please note that our modelling approach is not limited to a labeled dataset, but instead models the data distribution, no matter if classes are available or not. Labeled data just provides additional information, so that the false alarm rate can be minimized (see below). The techniques are also not limited to the simple activities chosen for this study, and the techniques can be adapted to more complex activities. Of course, several sessions of data, as used here, allow for a better fine-tuning of the models and are thus advisable.

Table 3: Comparison of the success rates and detection times for theft detection methods with suggested novelty configurations as described in Section 4.1 and Section 4.2 and a parameter optimized ν-SVM. Total success rate is calculated as the mean of user and thief success rates. Time is calculated as the mean of the successfully detected thefts.

	Parameter		***Success Rate***			***Time***
Method	α	γ	user [%]	non-owner [%]	total [%]	[s]
V-VAL	0.80	0.4	75.71	79.45	77.58	325
ENS$_1$	0.80	0.2	68.57	96.59	82.58	219
ENS$_2$	0.95	0.6	70.00	96.04	83.02	246
ENS$_3$	0.75	0.7	77.14	93.96	85.55	284
ENS$_4$	0.75	0.7	85.71	69.34	77.53	611
One-Class SVM	$\nu = 0.05$		84.29	36.04	60.17	1060

In Figure 7 such a system with all it's components is sketched. Visualized are involved components (dark gray rectangles), the data flow (dashed arrows), input source (the environment) and resulting output source (the smartphone's operating system).

Suppose that the overall system is consisting of a classification component and a detection component. Even though other algorithms might be eligible, the following explanations focus on a CMMs as model in conjunction with a penalty/reward-based Novelty Detection in the same manner as described in Section 4. As the classifier is a probabilistic one, information about certainty for each output are available. Whenever the classifier is certain enough about an activity prediction, the observed sample can be forwarded to the detection part of the system. In that part, the measure is updated and compared to the given threshold γ. Whenever the measure falls below that threshold, the device could sample a soundclip and gps-annotated picture (or video) footage and transmit it to a predefined location, server, backup- or rescue-address for the owner to review. Next actions could, e.g., be the shutoff of the device, the request for a pin, the activation of cryptographic code to secure sensible data or alike.

Two unknown numbers were just mentioned, one was a *certain enough* class prediction, the other one was a *given threshold* for novelty (or in this case theft-) detection. Concrete values are highly application specific, but usually a user would not want a hypersensitive smart device, but instead a very reliable theft detection (cf. Section 4.4). So one goal is a minimal false alarm rate, which can be achieved by defining a high class prediction certainty, along with a threshold, that matches the novelty detections sensitivity parameter η.

Those parameter estimations need data from non-owners, otherwise the adaptation to the user might not be specific enough (cf. Section 4.3, with a good detection of the rightful user but no more). Such data is usually not available on a user's device, but with cloud connected devices everywhere, it would be possible to push user-models into the cloud anonymously and make it available for other users. Especially when you think of a new device generation and only a fraction of users participating in this setup, everyone would benefit, as the novelty detection parameters could be adjusted very user-specific. In such a manner, every device of that new generation could be secured and autonomuously react to detected thefts.

A technical implementation of the overall system needs to make sure, that the following points are covered:

1. *Initialization.* The cold start phase of the system, is crucial for correct functioning. While the personalization and adaptation to the user is important, an average model (e.g., data collected by the manufacturer prior to release) for detecting everyday activities can be used as a good starting point. For a correct initialization, the system should also occasionally question the user for feedback, as, e.g., done in the *Active Learning* domain (cf., e.g., (Atlas et al., 1990)). During initialization, a set of activities that can be detected reliably for the device's user, should be fixed.

2. *Online operation.* After a successful initialization, the theft detection can start to work. Parameter-tweaking can be done via, e.g., non-owner models that are provided via the manufacturers or even a public cloud with movement models. To avoid confusion of the system or a watering of the model precision, the novelty detection should only receive data, when the classifying component is very certain. Again, this is a strong argument for the usage of simple activitiesm which can be detected very reliably.

3. *Detection action.* As soon as the novelty measure

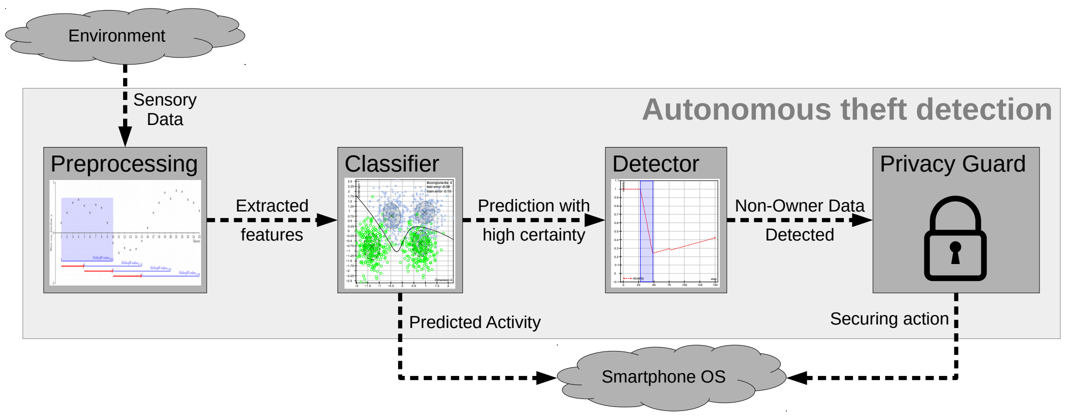

Figure 7: Schematic visualization of theft detection on a smartphone. Sensors signals come from effects in the environment (acceleration, sound, etc.) and are preprocessed. Prepared features are put into a classifier for activity recognition and into a detection unit. While the classifier predicts the user's current activity only, the detector identifies foreign data (based on the data model of the classifier) and triggers a privacy protecting guard if necessary. As a result, sensible information on the smartphone can be locked and made inaccessible to a thief.

is below the predefined threshold, the user action that was configured, should be taken. This could range from locking the device, via requesting a secure pin or answering a secret question to wiping all data, depending on the user's initial configuration.

6 SUMMARY & OUTLOOK

In this article, we based a novelty detection on top of an Activity Recognition (AR) process to realize a prototypical theft detection. Even though our experiments were based on five simple activities, the CMM is based on the structure of data and thus not confined to these exact activities. Followingly, the exact classes only play a role for the activity recognition part, but not for modelling a user by means of his data. This is very advantegous, because no matter how precise how many activities can be recognized: thefts can be detected based on very simple activities, that can be predicted very well and are nowadays included in every smartphone and fitness tracker from factory.

In Section 4 several techniques for detecting novel data in the input space were investigated and compared to a One-class SVM approach. The comparison revealed that there is no overall best technique, but that an implementation should be chosen with respect to an application specific requirement: the always present trade-off between detection accuracy and detection speed. Even though One-class SVMs are commonly used for the task of anomaly detection, even with a parameter optimization, we were not able to get the SVM to function comparably well as our GMM based novelty detection approach. A recommendation can be made for ensemble based techniques due to several reasons: First, each part of the ensemble can be trained independently, which allows for a speed up by parallelization. Second, less data is necessary to train each competetive ensemble member. And finally, even small ensembles (three members) reveal a very good and robust performance, when compared to other models that were trained on larger datasets or with higher computational effort. Based on the ability to detect data that deviates from a learned model, we sketched the usage of an autonomuous theft detection to secure user data in Section 5. Most remarkable is the fact, that even with just five daily activities, the detection works very well.

In general, SVMs perform reasonably well in Activity Recognition scenarios and are a good approach that could be focused more intensively (Lau et al., 2010). As an alternative to our performed grid search, better techniques like a Bayesian Optimization on training parameters might be worth considering. Towards theft detection, an even further spanned input space would be interesting, e.g. by incorporating more available sensors. Taking the theft detection towards a realization, it is necessary to conduct experiments with data not only from smartphones, but also from other smart devices (smart watches, smart infrastructure, ...). Finally, another interesting research question should aim at the structure of detected outliers: Are they random or do they form a new cluster in the input space? While random points might be a result of sensor noise, coherent points might be the result of something else. This question can be addressed by methods like CANDIES, as described in (Gruhl and Sick, 2016).

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