On Recognizing Abnormal Human Behaviours by Data Stream Mining with Misclassified Recalls

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ABSTRACT

Human activity recognition (HAR) has been a popular research topic, because of its importance in security and healthcare contributing to aging societies. One of the emerging applications of HAR is to monitor needy people such as elders, patients of disabled, or undergoing physical rehabilitation, using sensing technology. In this paper, an improved version of Very Fast Decision Tree (VFDT) is proposed which makes use of misclassified results for post-learning. Specifically, a new technique namely Misclassified Recall (MR) which is a post-processing step for relearning a new concept, is formulated. In HAR, most misclassified instances are those belonging to ambiguous movements. For examples, squatting involves actions in between standing and sitting, falling straight down is a sequence of standing, possibly body tiling or curling, bending legs, squatting and crashing down on the floor; and there may be totally new (unseen) actions beyond the training instances when it comes to classifying "abnormal" human behaviours. Think about the extreme postures of how a person collapses and free falling from height. Experiments using wearable sensing data for multi-class HAR is used, to test the efficacy of the new methodology VFDT+MR, in comparison to a classical data stream mining algorithm VFDT alone.

Keywords

Human activity recognition, data stream mining, classification

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1 INTRODUCTION

Recognizing movements and activities using technologies such as sensors, imaging, machine learning and data mining has become a prevalent computer science research top recently. One particular type of automated recognition is human activity recognition (HAR) that finds a number of useful applications, ranging from security monitoring [1], robotics [2], sports science [3] to healthcare [4].

In healthcare, getting to know the activities of a human subject using sensors helps protect the subject's privacy to certain extent, in lieu of imaging (e.g. CCTV camera). HAR by sensors captures the outline of a human figure, in the form of silhouette, without revealing the facial features when comparing to video camera. Judging from the received sensor data, which are usually in numeric forms describing the spatial and temporal information of a bodily action, the human activity is inferred. By using data mining algorithms, the continuous sensor data streams are fed to the system and analyzed for identifying what that activity is. For an example of healthcare application, elderly well-being monitoring in an old folks' home, taps on the combo of sensing and data mining technologies for ensuring the safety of an elder. The HAR in this application scenario involves detecting any abnormal behaviors beyond what a normal elder would do. It is generally known that elders move gently, their activities are generally mild compared to teens. In indoor the daily activities are typically, watching TV, walking, talking, cooking, and mapping etc. Abnormal movements include but not limit to sudden collapse, abrupt, rapid or violent actions and likewise would trigger an alarm, requesting for immediate attention to the subject.

At the algorithmic level, the data mining software program learns a human activity using supervised learning – training samples with already labelled activities are supplied to the data mining program, for inducing a generalized model which knows about the mapping between the multivariate input variables to the specific activities. Once the supervised training is completed, the trained model is ready to put into test for classifying unseen data instances into activity labels.

Recently, many research papers focus on increasing the accuracy of a classifier by improvising the classification algorithms for HAR. Techniques at different levels were used to improve the HAR classification. They vary from removing outliers [5], hybridizing sophisticated learning methods to using parallel processing [6]. In common, these research progresses look into the possibilities of enhancing the classification accuracy. In this paper, we propose a novel methodology in HAR called Misclassified Recall (MR) for patching up the training data, which is in contrary to the other earlier methods. Instead of searching for a better classification algorithm, MR turns to the classification errors, analyses the misclassification, and it prudentially attempts to relinquish the subset of training dataset that caused the misclassification. By this approach, it takes a preemptive measure to avoid misclassification in subsequent situations where the same or similar type of training sub-dataset is detected.

MR is particular suitable for data stream mining where the full dataset is not assumed static but continuous. Using fast and incremental pre-processing mechanisms in misclassification detection, such as Bayesian network and K-means, MR that is coupled with Very Fast Decision Tree in data stream mining are identifying the misclassified errors and retraining / refreshing the main classifier on the fly.

The paper is structured as follow. Section 2 reviews similar research papers which have probed into the data mining errors for gaining insights for future improvements. Our new MR methodology is described in Section 3. A simulation experiment, using empirical HAR dataset is tested under MR. The results are discussed in Section 4, then the paper is concluded in Section 5.

2 RELATED WORK

The research progresses pertaining to data mining techniques [7] for HAR are reviewed in this Section. HAR is a rather broad topic with the goals of understanding the subject's actions in relatives to the environments and the context of the scenarios [8]. There are different types of HAR, which can be categorized to mainly sensor/video or vision-based, single/multi user activity recognitions. The capacities of recognition vary in levels and resolutions of the actions and activities, depending on the users' requirements and applications. It could be at a very detail level, like gait analysis [9], which is some assessment tool for studying biomechanics in order to investigate the muscle dynamics and solving movement-related mobility problems. The recognition techniques range from logics and probabilistic reasoning [10]. These techniques are applied to model the activities, quantitatively; from the model, knowledges or clues about the action plans and activity purposes are deduced. Some typical modeling tools for such tasks are, Hidden Markov Model [11] which is generative, another popular choice for modeling sensor data in HAR is Dynamic Bayesian Networks [12].

Lately data mining based approaches have proliferated in HAR as such machine learning techniques become popular and affordable. Data mining based approaches took a slightly different perspective from other modeling tools which model the activities explicitly from the sensor data. Rather, data mining techniques attempt to formulate a generalized pattern-oriented classification model. Information from space and time, and relativity to the joint movements, are fed into training up a classification model, typically a decision tree or support vector machine or neural networks. When the model matures, it is put into use in application embracing arrival of new sensor data. A typical work is reported in [13] which compares the performances of several classical data mining algorithms using publicly available inertia sensor data from smartphone. They aim to achieve real-time analysis upon incoming sensor data for applications related to healthcare monitoring disabled or elderly people, based on their daily activities. Those activities that usual happen are considered normal, and vice-versa. The goal is to distinguish the abnormal ones from the normal activities, using binary or multi-class classification algorithms. Similar works with the same goal are [14, 15, 16] which applied popular classification algorithms on accelerometers data. These works have in common an objective of producing a classifier as accurate as possible with a prime priority in pushing the classification accuracy to its maximum, either by trying out a collection of algorithms and picking one, or by feature engineering [17] that selects the best subset of features for maximum classification power.

For the research works in the computer science literature that aim at solving HAR problems, traditional data mining techniques have been widely used – they include mostly, feature extractions, feature selection, data pre-processing, and classification model induction, etc., which are typical KDD processes. Lately, some research momentums for HAR embark on data stream mining [18], change detection (e.g. the effects of window size are investigated in [19]) and incremental outlier detection and removal [20]. This relatively new category of data mining based-approached gave hope to achieving real real-time big data stream analytics. More importantly for many monitoring types of applications, the data mining models are expected to be adaptive, accurate and be able to learn new concepts on the fly. Traditional data mining algorithms, on the other hand, are designed for batch processing and full scale learning. As a result, this motivates a new breed of research in data stream mining algorithms which need to be fast and resilient in case of concept drifts or changes in the application conditions. Therefore, this serves as the impetus for the research reported in this paper.

3 PROPOSED MISCLASSIFIED RECALL

Misclassified Recall (MR) is a proposed mechanism under a new novel data stream mining strategy, where misclassified errors are examined and rectification may take place. As shown in Figure 1, MR is an auxiliary data processor in a two-steps learning process. The sensor data are streaming in as live feeds. The data streams arrive in bulks as a sliding window holds them, moves them to MR and clears the window one at a time. Data that arrived and sent for learning will not be reused, as the data stream is continuous and it amounts to infinity.

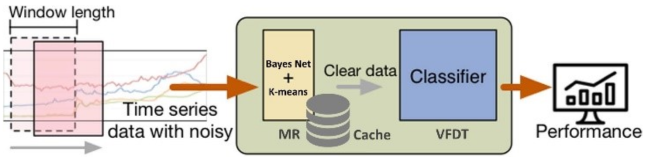


Figure 1: MR-VFDT Model.

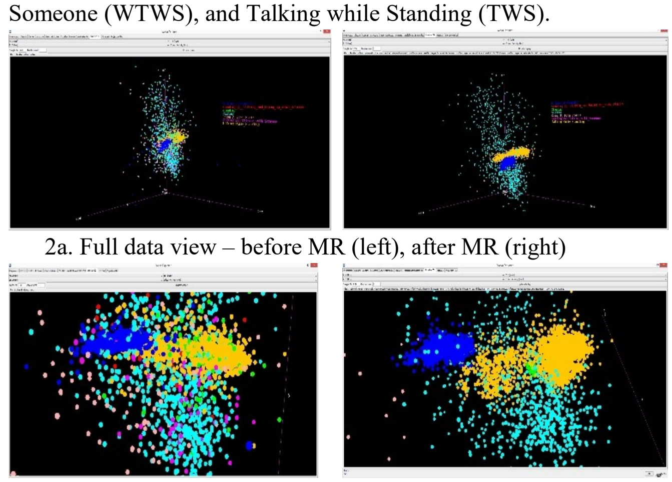
3.1 The Overall Concept

A generalized model based on a classical data stream mining algorithm, called Very Fast Decision Tree (VFDT) [21] is used as a main classifier. Instead of learning from the first-hand data which may contain noisy information, VFDT learns from the processed data received from MR. In this way, the original data feed is anticipated to contain noise, but the noise is filtered through MR. Noisy data may come from one of the following reasons: outliers, missing/wrong data values by momentary accidents or otherwise, and data that were not labelled correctly for supervised learning. The first two categories of noises are common and easy to notice. Many methods have been studied before in tackling them, such as removal or substituting the values with some average or special values. The last type of noise, is rather subtle. They may appear normal until they were fed into the model induction process, and the accuracy deteriorates. In the context of HAR, such noisy data in the training samples account for the following examples [22]: ambiguous activities, complex activities, and unknown movements. Ambiguous activities are those that appear like more than one type of actions, but somewhere in between. For example, squatting-down-or-up is between standing and sitting. The faster the action happens the more ambiguous it may seem. Another example is full body leaning while standing; if sensor data are collected solely from a moving human body without regards of the surrounding objects, the posture may appear somewhat like a combination of standing, sitting and even lying down, depending on the angle of incline in the leaning posture. Same data patterns/subsets are labelled with different activities. The other type of noise in HAR is due to the complex and composite actions, e.g. walking while talking, standing while cooking, walking up/downstairs while jogging etc. Often more than one type of actions is tightly coupled with another one or one gets embedded into another in these complex activities. They make it difficult for a classification algorithm to generalize a recognition model. The last type of data is totally unseen or undiscovered. These actions do not have explicit records or even labels in the training data. But they do happen in rare occasions, or they can happen all the times but too subtle to get noticed. For examples, collapsing, dropping, or tripped/slipped while walking, and shaking one's hand, bending one's fingers or touching ears upon some emotional changes. They may not actually be outliers where by definitions outliers occur rarely. A classifier lacks of training in recognizing this kind of less-known actions. In general, from the perspective of a classification algorithm, training/testing with such so-called noisy data would lead to classification errors. Often, the errors are neglected as they can be easily presumed to come from the deficiency of the data mining algorithm itself. However, in this study we take a different view of the problem, focusing on the misclassified data in place of the algorithms.

MR has a filtering mechanism which detects and removes data instances which would potentially impair the model induction – this is important as some data stream mining algorithm is very sensitive to even the slightest incorrect training samples. As an auxiliary filter, MR tests the incoming training data for erroneous classification. The monitored accuracy or error serves as an indicator if further action is required. A successive period of decline of accuracy, in relative to some user-defined threshold, signals a series of counteractive processes. Firstly, a prolonged decline of accuracy implies concept-drift occurred in the data stream. Continuing to learn from the incorrect data for the changed concepts is counterproductive which needs to be paused. The halt shields the already built VFDT decision tree from being confused, sustaining certain level of accuracy. Given the misclassified errors as measures of when they occurred, a subset of training data which are suspected to be noisy is checked against the clustering results of the accumulated data. A cache is used as shown in Figure 1 to store up the past data for clustering.

3.2 The Supporting MR

In particular, a Bayesian Network and K-means clusterer are used in the MR, for early detection of classification power dips and identifying what type of noise it might be, respectively. These noisy data would be removed prior to VFDT in the main classifier. The data after being processed by MR is called clear data. Figures 2a (full view) and 2b (close-up) visualize the training data in their original form and in their processed form after MR, respectively. The HAR dataset [21] that was used in the experiment is the one that extracted from a wearable smartphone where the collected spatial data in x-y-z axis are labelled into multi-class activities. They are: Working at Computer, standing up Walking and Going up down stairs, Standing (STD), Walking (WKG), Going Up Down Stairs, Walking and Talking with Someone (WTWS), and Talking while Standing (TWS).



2a. Full data view – before MR (left), after MR (right)

2b. Close up data view – before MR (left), after MR (right)

Figure 2: Visualizations of the HAR datasets before and after MR process.

It is observed that there are many interleaving and tangled data of different activities in the original dataset. The most obvious case is the data points of WTWS mixing with STD. They cross and exist in different spatial places of one another. After MR, the data of different activities become more homogenous. The overlapping has reduced to certain extent. The motivation of using K-means is the fast processing speed which is essential in data stream mining environment. Clustering groups data points that are similar to each other. In case of having a new activity that is previously unknown emerges, or case of umbigious activities, data that are similar within the same group can be separated out and form its own class of activity.

Figures 3a (top) and 3b (bottom) show the K-means clustering results. The original data has several places of major overlapped, such as WTWS and WKG, WTWS and STD, and WTWS and TWS etc. This is mainly due to the data of WTWS contain similar postures as in WKG, STD and TWS.

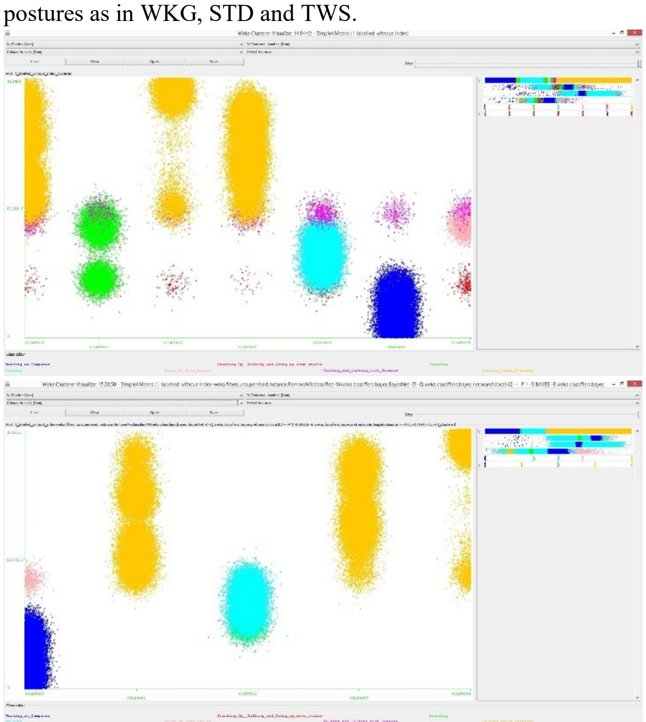


Figure 3: Visualized results of K-means clustering in MR-VFDT

3.3 The Model Formulation

The incremental learning algorithm in use, VFDT [21], was solicited for the purpose of achieving the most accurate classifier and Bayesian Network (BN) for pre-emptively marking out the relevant data from the data stream for decision rule induction. Readers are referred to [21] for details about the VFDT model.

The design of MR-VFDT comprised of two classifiers: the main tree classifier (*VFDT*) and the auxiliary rapid classifier (*BN*). While *BN* monitored the fluctuation of the data streams and all the harmful element in model induction by monitoring its testing performance such as outliers, prolonged misclassified instances, concept-drift, etc., *VFDT* maintained the global memory of the overall classification task. Concept drift is a phenomenon of fundamental changes in the underlying concepts among the data, usually due to some major events. Changing the type of activities in HAR is an example, from sports management to elderly's healthcare.

VFDT was responsible for doing the final prediction; both *VFDT* and *AT* were implemented using fast incremental learning methods, although *BN* tried out the incoming data first before deciding whether *VFDT* should be updated with the data. In this way, *BN* was a cache-based classifier that updated its Bayesian probabilities by processing the data instances that were locally cached in a sliding window of fixed size, W. During each cycle, W was reloaded with fresh data and *BN* was refreshed with these data. Upon arrival of the new data $(X_i \mid y_i)$ at the i^{th} iteration, where X is a multivariate array of m factors, $X = (x_1, x_2, \dots x_m)$, y is the actual label value, the classification function is $\overline{y_i} = f(X_i|y_i)$, where $\overline{y_i}$ is the predicted outcome given X_i. Counters were used to store the misclassification records as signals to indicate whether a refresh on *BN* was needed and how relevant the data that arrived in the past successive windows were. *VFDT* continued to test the samples and absorb minor fluctuations of the predictive power due to temporal fluctuations in the quality of the data in the data streams.

During the data stream mining process, *VFDT* and *BN* predicted their own results separately. The misclassification counts were updated as follows:

$$VFDT(X_{i-1}) \rightarrow \overline{y_{i-1}} \begin{cases} = y_i \Rightarrow Count_{+}^{VFDT} = Count_{+}^{VFDT} + 1 \\ \neq y_i \Rightarrow Count_{-}^{VFDT} = Count_{-}^{VFDT} + 1 \end{cases} \quad (1)$$

$$BN((X_{i-1}) \rightarrow \overline{y_{i-1}} \begin{cases} = y_i \Rightarrow Count_{+}^{BN} = Count_{+}^{BN} + 1 \\ \neq y_i \Rightarrow Count_{-}^{BN} = Count_{-}^{BN} + 1 \end{cases} \quad (2)$$

After comparing the predicted and actual results at each cycle, the counters were aggregated into a variable for each *VFDT* and *BN*.

$$Count_{\Delta}^{VFDT} = Count_{+}^{VFDT} - Count_{-}^{VFDT} \quad (3)$$

$$Count_{\Delta}^{BN} = Count_{+}^{BN} - Count_{-}^{BN} \quad (4)$$

A coefficient c_i was used to represent the predictive power of the current *BN* and the overall *VFDT* pertaining to a class y_i at i^{th} cycle.

$$\frac{\sum_{\alpha=1}^{A}\sum_{\beta=1}^{B} s_{\alpha,\beta,i}}{|W| \times i} = c_i \times \frac{Count_{\Delta}^{BN}}{Count_{\Delta}^{VFDT}} \quad (5)$$

where $s_{\alpha,\beta,i}$ is a statistical count of sufficient instances that have come and they belong to their respective classes α and β. Once *BN* was updated, W was flushed and the corresponding counters of *VFDT* were reset. Thus, the coefficient c_i can be defined as:

$$c_i = \frac{Count_{\Delta}^{MT} \times \sum_{\alpha=1}^{A}\sum_{\beta=1}^{B} s_{\alpha,\beta,i}}{Count_{\Delta}^{AT} \times (|W| \times i) + 1} \quad (6)$$

In general, the smaller the coefficient value c_i, the higher the overall accuracy for *VFDT*. The coefficient can be used in marking out the portion of data samples that were relevant and so can sustain the predictive power of *VFDT*. A simple logic could be set, such as portions of data were only considered useful when the predictive power of *VFDT* was inclining, taking the value of c_i as a reference.

4 EXPERIMENT AND DISCUSSION

4.1 The Setup

A simulation experiment is designed and run for testing the efficacy of the MR data stream mining methodology. The objective is centered at comparing the data streaming performance between the original data stream mining algorithm (VFDT) and the improved data stream mining algorithm with MR (MR-VFDT). HAR [22] is chosen as a case study, as accurate and real-time recognition of human activities is very important in healthcare society. The analytics must be fast and reliable (accurate), in order to support monitoring elders' safety in time critical situation. In the training/testing dataset, daily activities of a person are labelled with 3-axial spatial information, the instances are sequentially ordered.

The hardware is of an Intel i7-4785T x64-based CPU with speed of 2.2 GHz, equipped with 8Gb RAM and 64-bit Windows 8.1 Operating System. The software environment is open-source Java-based Massive Online Analysis (MOA) software which provides a programmable and extensible platform for implementing data stream mining algorithm. The HAR dataset is subject to the MR-VFDT model and VFDT model alone respectively. A default window size of 1000 is used. The performance sampling rate is a test per 100 instances. By the nature of data stream mining, the performance accuracy is measured in a test-then-train fashion, which is in contrast to fully train-then-test as in partitioning type of traditional data mining. This evaluation scheme is common in data stream mining experiments, it is also called interleaved 'test-then-train' evolution or prequential test. The concept is to use each instance first to test the VFDT or MR-VFDT model, and then to see if update is needed for refreshing (or further training) the model. In MOA the evaluation option called Prequential Evaluation is selected which is suitable for simulating the tests of performance of online classification model for recognition human activities in real time. It measures the performance of the model including the current accuracy, speed of model update (for building or refreshing the decision tree), memory usage and the current decision tree size, on the current sliding window of recent instances.

4.2 Experiment Results

The statistics for the accuracies of the models, which we term it resiliency accuracy are tabulated below.

Table 1: Frequency of Special Characters

	Average %	Min %	Max %	Standard deviation
VFDT	93.31987692	12.9	100	16.56468973
MR-VFDT	99.74313846	75.1	100	1.522363261

A significant accuracy gain can be seen from Table 1. Though both original and MR-VFDT model can achieve maximum of 100% accuracy most of the time, the average accuracy of MR-VFDT has significantly increased from 93.3% to 99.7%. The 0.3% of the MR-VFDT model is possibly due to momentary jitters as some true outliers are observed from Figure 2a, and the transition period of the change of activities. The drop of accuracies to minimum however for the original VFDT is quite severe at 12.9%, making the HAR model almost unusable. The standard deviations differ greatly, 16.5 for VFDT and only a fraction of it at 1.5 for MR-VFDT.

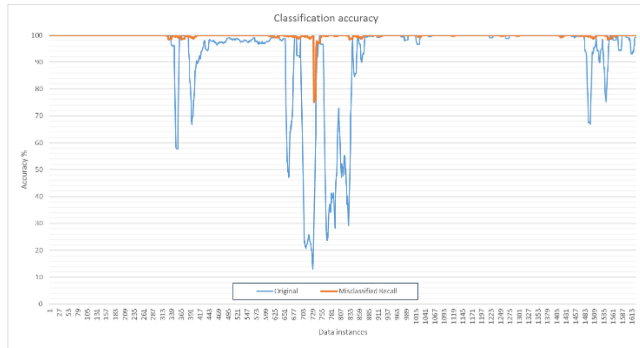


Figure 4: Resiliency Accuracy.

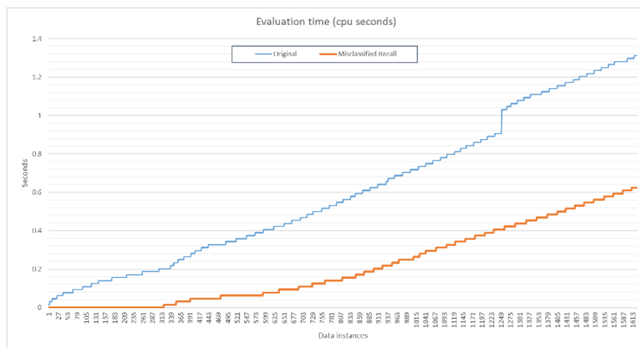


Figure 5: Speed (inverse of CPU time consumption).

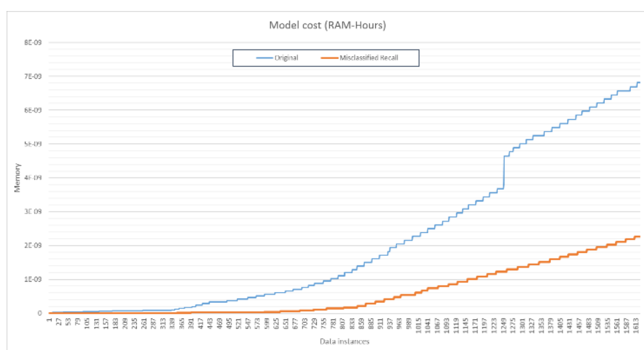


Figure 6: Memory.

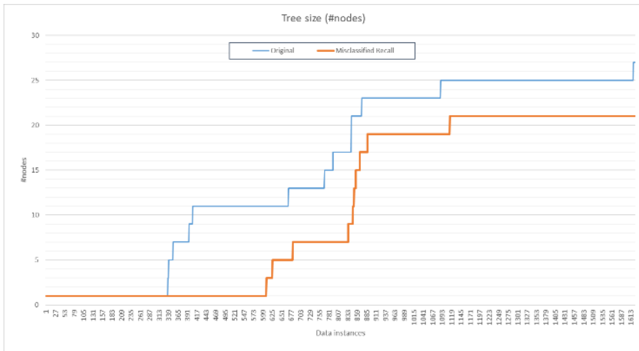


Figure 7: Tree size.

The performances of the two models, namely original VFDT and Misclassified Recall for MR-VFDT are shown in temporal domain, in Figures 4, 5, 6 and 7.

In Figure 4, the accuracies of both model are present in time domain, that offers a longitudinal view of how the classifiers perform in real-time as the data fed in. Both models suffered some accuracy drops along the way. From these patterns, the accuracy drops coincide with the changes of the activity levels - the activities started with sitting, changed to standing, walking and WTWS. In particular, WTWS has affected the most in the original VFDT because many confusing instances that inter-lapped between the two classes exist. The confusing training instances deteriorate the VFDT model, pushing down the accuracy to the minimum 12%. This is indicated in the middle part of the graph in Figure 4. On the other hand, MR-VFDT is more resilient than VFDT, for its accuracy dips upon change of activities, but it recovers quickly after that. The MR is showing its shielding effect in preventing the confusions from the misleading instances.

The speeds, memory consumptions and decision tree sizes, as shown in Figure 5, for the two models escalate in general as new instances stream in. Overall, MR-VFDT is able to achieve stable accuracies at higher speed, at lower consumptions of memory and resulting at more compact tree sizes. Although a large scale experiment has yet to be conducted, these preliminary results show that MR-VFDT has potential to scale better than VFDT, judging from the gradients of increase. For instance, for the model update time consumption graph in Figure 5, the gradient for the VFDT curve is 8x10-4 whereas the gradient for MR-VFDT is half of that of VFDT at 4x10-4. The curve gradient for the memory usage for VFDT is 4e-12, and for MR-VFDT is 1e-12 which is just a quarter of it. These imply that MR-VFDT is more scalable than VFDT in terms of time and memory consumption. As in Figure 7, the growth of the decision trees follows a similar pattern, while MR-VFDT always have a smaller tree size. This is due to the fact that unnecessary tree mode expansion (hence tree growth) is avoided from the confusing learning cases for MR-VFDT. No extra tree branches were formed due to those error cases.

5 CONCLUSIONS

Researchers recently turn their attention to human activity recognition (HAR) as it is the underlying analytics in monitoring and detecting applications. HAR found many application areas such as safety monitoring for elders which is important in aging society. An improved version of Very Fast Decision Tree (VFDT) is proposed in this paper, namely VFDT with Misclassified Recall (MR), or VFDT-MR. MR is a dual purpose, one is serving as a pre-emptive performance tester which tests whether the incoming training data instances are to be harmful to the main VFDT, in a 2-steps data stream mining mechanism. The other purpose is for post-learning. The misclassified instances are clustered in a temporary archive, which provides insights to users on which and how instances are classified to wrong classes similar to confusion matrix. A simulation experiment is performed over wearable sensing data for multi-class classification in HAR. The experiment tested the efficacy of the new methodology VFDT+MR, in comparison to VFDT which is a classical data stream mining algorithm alone. The results in different performance aspects, including accuracies, time and memory consumptions unanimously indicate that MR-VFDT is more resilient in data stream mining training datasets that may contain overlapping concepts; shorter time and less memory consumptions are observed, implying MR-VFDT is more scalable than VFDT. To sum up, the contribution of this paper is a conceptual model of data stream mining with capability of screening the incoming training data feeds. Thereby early performance degradation could be detected, delivery of the misclassified instances to the main classifier could be paused, and stored up for post-processing. Fast clustering is performed to investigate whether the misclassified instances are simply momentary noise or due to inappropriate labels in the training data. Potentially this work can serve as a blue-print for building a holistic data stream mining model which pre-emptively examines and sorts out the causes of misclassification (outliers [20], wrong labels, concept drifts [23], etc.) with corrective actions, for subsiding the errors of the main classifier during stream mining operations to minimum.

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