Universite de Lyon / Universite Jean Monnet

Master in Machine Learning and Data Mining

Developing Anomaly detection for elderly people, Oriented IoT Devices.

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1 Brief Company Introduction

Novin is a startup company located at No 7 Rue Pablo Piccaso Siant-etinne, they propose to manufacture a smart walking cane that can detects any unusual situation (fall detection, lower activity, etc.), to be used by the elderly people, the cane is suppose to be able to automatically alerts caregivers and family member's without any action from the user if needed. Although as a startup company they are still on the design phase so their's no data on ground for my analysis, in view of this i have decided to start my study from ground zero and hope to gather some data on my own for the analysis.

1.1 Objective of this study:

The aim and objective of this work is to investigate and detect anomaly associated with ambulation in elderly people, in addition to this, we will strive to learn the ambulation pattern of the elderly in order identified some diseases common with the elderly before getting to advanced stage and make adequate recommendation for the patient to visit a physician.

All codes for this projects are available on my github account at :

`https://github.com/surajrasaq/Anomaly-detection-for-elderly-people-Oriented-IoT-Devices`

2 Introduction

The develop world has witness a tremendous increase in the population of the older people while the developing world are not left behind, quality of living has generally improved worldwide and people now tend to live longer. It is estimated that this trend might continue to soar with the [1],2013 United Nation projection of about 2523 billion worldwide population of older people by 2050.

Because people experience aging in a unique way, it makes it very difficult to evaluate the behavioral pattern of the elderly people. However, proper knowledge and understanding of the way our senior citizen behave will allow them to continue to live a meaningful life and to make valuable contributions to the society. Generally socially active elderly people were more likely to avoid disabilities associated to daily activities when compared to people who are not socially active, In addition to this, Unadulterated peace of mind will be guaranteed for the older citizen with the awareness that they are constantly been watch over when in need of emergency.

2.1 Elderly Activities:

Activities for daily living (ADL) has been used frequently to refer to the daily living and survival of an individual but recent usage of this terms are mostly common for the aged people, elderly people are in constant in need of help which may warrant a move to seek help from outsider or ultimately entering a nursing home, now the question arise, how do we evaluate the need of an individual? do we ask them verbally or understudy their behaviors. Advanced in technology and the use of IoT devices enable us to use latter options also fast increase in elderly population has necessitate the growing demand in many applications such as health-care systems for monitoring the activities of daily living and the use of context aware computing systems using smart devices are becoming more popular especially in the field of anomaly detection. Now it is possible to track occurrences of regular behavior in order to monitor the health and find changes in activity patterns and lifestyles [2], for elderly or people with disabilities, ADL monitoring can be used to detect the likely hood of an individual health challenged also used to study the pattern of an individual daily activities.

2.2 Some common and identified behavior in elderly people

Behavior is an individual things which might be difficult to generalize, getting a common ground might be tricky, some study has it that an older person will probably act the same way he or she has been acting when young but in reality aging affect us differently, sense organs depreciate as we are growing older hearing loss are frequents, visions can depreciate and some people may even experience cloudy taught which is a direct results of memory loss.Therefore its save to conclude that elderly activities are highly connected to health statues of the individual. This is why disability researchers have devoted considerable attention to developing measures that tap practical dimensions of everyday life as a way of measuring a person's physical functioning, activities of daily living are increasingly being used as the way to measure disability and ADL estimates will differ for good reasons, meaning there is no one right estimate [3], Finally, activities of daily living (ADLs) can be broken down in different categories.

- Sanitation.(Cleaning and regular home choir)
- Personal Managements.(Ability to be able to organize and manage self)
- Feeding.(Capability of self feeding without Assistance)
- Dressing (Ability to be able dress self)
- Ambulating. (Ability to be able to move or walk independently)

2.3 Ambulation and the risk of falling

The primary aim of this study is to investigate anomaly associated with ambulation in elderly people, in order to properly evaluate this, first we need to study ambulation and risk associated with it, then try to identified and detect anomalies that are connected with them. Ambulation is the ability to move from one position to the other, it provides an array of physical and mental benefits for the elderly which range from muscle strengthen, relief from pressure and joint and also generally promote the feeling of independence. Some old people are able to ambulate by themselves while some need assistance from experts others may require assistive devices such as gait belts, canes, and walkers.

Mobility has been recognize as a very important factor which can serve as a natural remedies from feeling isolated and greatly reduce anxiety and depression it's also serve as a form exercise for the elderly, but this does not come without a risk, due to the loss of bone mass or density in elderly people, the tendency to fall is high even with the use of walking sticks, fall has been describe as a leading cause of injuries and possibly death among the senior citizen it can also lead to fear of further falling and ultimately lead to depression.

Recently fall among the elderly has attract a growing interest in the field of artificial intelligence several studies have demonstrated different technique to tackle this menace and possibly provide a visible solution. Falls are defined as accidental events in which a person falls when his or her center of gravity is lost and no effort is made to restore balance or this effort is ineffective, the underlying cause of falls could be a seizure, a stroke, a loss of consciousness or non contestable forces.[4], the prevalence of falls is known to increase sharply with age[5], more than 2.1 million falls was reported in 2007 and they were the leading cause of nonfatal injuries among persons 65 years or older treated in hospital emergency departments in 2008 [6], aside falls other related gait behavior are being understudy especially syncope, stumbling, and abnormal bend down.

Most cases of fall often go without reporting once a patient has been taken to the hospital people tend to forget about the incidence, different way of preventing fall has been suggested by experts. We can reduce the possibility of an unfortunate fall by removing any and all items that may present themselves as obstacles and ensure that the patient is wearing appropriate supportive shoes or footwear, but the question is can we totally prevent fall? The answer is NO but we can device a mean of reporting it and the patients can get the necessary intervention at the appropriate time.

2.4 Anomaly Detection and Classifying Fall as an anomaly

How do we classify fall as anomaly? up till this moments no dataset of real-world fall is available [7], whereas detecting falls and alerting the appropriate quarters will be a plus and sources of confidence building among the elderly, moreover treating fall or no-fall as a binary case might not be too effective due to individual behavioral difference, therefore we need a more robust method in order to be able to properly classify fall. [8], has classified falls detection in to context-aware systems and wearable devices, the former uses sensors such as cameras, floor sensors, infrared sensors, microphones and pressure sensors deployed in the environment to detect fall while the latter employ the use of miniature electronic devices like accelerometers and gyroscope that are worn by the users, in addition to this uses of inexpensive smart devices embedded in cane, wrist-band, neck-lace and shoes can also do this magic.

Motion detection are mostly explore in detecting fall and the use of accelerometer and gyroscope has been used in most of the aforementioned wearable detector, but we still need an intelligent machine learning technique that will analyze data taken from this devices to identified and segregate ordinary fall from accidental falls. Another challenge is recognizing the recovery moments, yes accidental fall could happen but when the user recover (time range is needed here) and pick up the device back it should be able to feed back the appropriate quarters on the recent recovery.

Traditional anomaly detection technique could be train to learn fall and also learn in broad manner the daily activities perform by the elderly people, but actual related data will be better fit for evaluation. Anomaly detection system is vital and must be reliable, effective and efficient, the precision must be accurate because of risk involve when the user is in trouble, it should act promptly by notifying the people involve, type 1 error can be tolerated to some extent but type 2 error should be totally avoided, study have found that the number of false positives per day in real scenarios are in the increase [9], depending on the specific technique and this are leading to device rejection, therefore, to improve the level of penetration of these systems it is essential to find a robust anomaly detector where fall can be treated as a life threaten anomaly and can trigger strong alert.

Fall detection techniques could be split into two main families: Vision based approaches and Non-vision based approaches [10], vision-based fall detection methods are usually rested on information captured from images and videos, while non non-vision based uses sensors such as acceleration and vibration sensors. Most popular fall detection techniques exploit the use of accelerometer data as the main input to discriminate between falls and activities of daily living (ADL).

Threshold approach based on accelerometer is common, here an alert is triggered according to the pre-define threshold which is measure by peak value during a fall also a more sophisticated and more reliable way is to employ the services of machine learning algorithm [11], several studies has explore the use of machine learning technique to classified fall, a particular draw-back to fall classification is that traditional approaches to this problem suffer from a high false positive rate, particularly, when the collected sensor data are biased toward normal data while the abnormal events are rare [5]. we can conclude that classifiers are said to sensitive if they classified anomaly as not normal and specific if ADL is classified as ADL [12].

3 Review literature based on existing study

Several study have been carried out in order to segregate what can be termed normal and abnormal behavior among the older citizen, most of this studies are based on heuristic analysis, discriminative and generative methods. Sometimes all this methods may be combined for better classification. However, some of this method are not so comfortable for the users they are made to wear various sensor on their body including neck, wrist, waist and even foot, moreover a vision based approach might be intrusive on the privacy of the user and the fact that cameras are not suitable for bathroom even complicate the uses of this method, majority of this method are based on falls detection which at times report more false positive and lead to mistrust of this devices among the caregivers and relatives, following are some of the existing method and technique adopted in learning the activities of daily living of the elderly people.

3.1 Wagner file analysis

[11], A cloud based health care system is proposed in this paper for the elderly using an incremental SVM (CI-SVM) learning with tri-axial acceleration sensor embedded to capture the movement and ambulation information of elderly. The collected signals are first enhanced by a Kalman filter and the magnitude of signal vector features is then extracted and decomposed into a linear combination of enhanced Gabor atoms. The Wigner-Ville analysis method is introduced and the problem is studied by joint time-frequency analysis.The original abnormal behavior data are first used to get the initial SVM classifier. And the larger abnormal behavior data of elderly collected by mobile devices are then gathered in cloud platform to conduct incremental training with the CI-SVM learning method, the knowledge of SVM classifier could be accumulated due to the dynamic incremental learning.

Activity recognition using fusion of multi-sensor was adopted by [12], two sensors are fused for coarse-grained classification in order to determine the type of the activity, zero displacement activity, transitional activity, and strong displacement activity, then a fine-grained classification module based on heuristic discrimination or hidden Markov models (HMMs) is applied to further distinguish the activities. **Slight change of air pressure** was used by [13] to detect vertical movements and classification was achieved using one acceleration sensor and one air pressure sensor attached to the waist of user to detect the moving styles of going up/down the stairs or in an elevator.

3.2 Conductive textile based electrodes

[15] Uses electrodes integrated in to wearable garments, capacitance change inside the human body was measured, and such changes are interrelated to motions and shape changes of muscle, skin, and other tissue, which can in turn be related to a broad range of activities and physiological parameters. Activities such as chewing, swallowing, speaking, sighing (taking a deep breath), as well as different head motions and positions was learned.

3.3 Artificial Neural Networks

(ANNs) in conjunction with a simple kinematics model was used by [16] to detect different postural transitions (PTs) and walking periods during daily physical activity. Inter-connected neurons are capable of automatic learning based on experience and approximating non-linear combinations of features for pattern recognition. [19] **Utilize the infrared (IR) motion sensors** to assist the independent living of the elderly who live alone and to improve the efficiency of their health care. An IR motion-sensor-based activity-monitoring system was installed in the houses of the elderly and used to collect motion signals and three different feature values, activity level, mobility level, and non-responsive interval.

Medrano et al [14] try out the use of a machine learning technique based on one-class classifier that has only been trained on ADL to detect falls as anomalies with respect to ADL. their experimentation was conducted with a k-Nearest Neighbor (kNN) classifier. Although they conducted their studies on simulated data by volunteers, this participant simulated about eight different type of falls (forward falls, backward falls, left and right-lateral falls, syncope, sitting on empty chair, falls using compensation strategies to prevent the impact and falls with contact to an obstacle before hitting the ground.) using smart phone embedded with accelerometer and then try to learn one-class kNN and subsequently they try to evaluate their model on two-classes Support Vector Machine (SVM) with a promising results, however they conclude that accelerometer provides detailed information on behavior such as physical activity and inactivity.

they concluded that the information can be used to measure more comprehensive relationships among movement frequency, intensity and duration but anomaly detection is not visible, this conclusion might not be entirely correct because SVM is an highly computational demanding model during training which cannot be met using mobile phones with limited computation power, also smart phones are not design for safety applications.

[17] This paper tries to address fall from statistical point of view as an anomaly detection problem. Specifically, the paper investigates the multivariate exponentially weighted moving average (MEWMA) control chart to detect fall events. This approach is based on visual monitoring, where they used image processing scheme to detect fall and trigger alert. Here they completed treat falls as binary where anomaly occurs at the moment of the fall. When a person falls, a fall detection system would declare it as abnormal action. Mubashir et al [18], categorize falls in to falls from walking or standing, falls from Standing on supports, e.g., ladders etc., falls from sleeping or lying in the bed and falls from sitting on a chair, but if we are to follow this classification then the focus of this studies will be on the first two since we are dealing majorly with ambulation as a sub-set of ADL.

Noury et al [19], designed a smart fall sensor, the software application transmits the data remotely through the network as well as exploiting data locally. The data are further analyzed to determine the current state such as lying after a fall, sleeping, walking, etc. Nyan et al. [20] Distinguished backward and sideway falls from normal activities using gyroscopes (angular rate sensors). The gyroscopes are securely placed on different positions, such as underarm and waist. This angular rate is measured for normal activities and falls in lateral body planes. A high speed camera is used to capture video image sequences of motion for body configuration analysis in the event of a fall, the fusion of high speed camera images and gyroscope data is synchronized, and gyroscopes rely on the idea of acceleration thresholds to differentiate fall events from normal activities.

3.4 Marker-based stigmergy

Stigmergy [21] based approach can be employed by exploiting both spatial and temporal dynamics because of it's intrinsically embodies by the time domain. Moreover, the provided mapping is not explicitly modeled at design-time and then it is not directly interpretable which offers a kind of information blurring of the human data, and can be enhanced to solve privacy issues being experience in some model. Furthermore, analog data provided by marker based stigmergy allows measurements with continuously changing qualities, suitable for multi-valued classification. **Alessandra Moschetti et al** [22] compare unsupervised and supervised methods in recognizing nine gestures by means of two inertial sensors placed on the index finger and on the wrist. three supervised classification techniques, namely Random Forest, support vector machine, and multilayer perceptron, as well as three unsupervised classification techniques, namely k-Means, hierarchical clustering, and self-organized maps, were compared in the recognition of gestures made by 20 subjects. The obtained results show that the support vector machine classifier provided the best performances (0.94 accuracy) compared to the other supervised algorithms.

Faria et al [23], uses probabilistic ensemble of classifiers (DBMM) with a local update of weights designed for activity recognition, their approach is based on confidence obtained from an uncertainty measure that assigns a weight for each base classifier to counterbalance the joint posterior probability. A dictionary learning algorithms K-singular value decomposition (K-SVD) is used to learn human activities [21] by exploring sparse signal representation.

4 Method and Technique

Although none of the existing technique has explore the use of smart cane been proposed here to detect anomalies in ADL, this novelty has introduced a new dimension in to this field as cane or walking stick is a natural aids for ambulating among the elderly and disable, we presume this will be more convenient and more comfortable for the users compare to the wearable devices which may be intrusive and awkward. The system is composed of perception layer, data collection and storage layer, smart learning platform, and intervention layer. Fig [1] depicts the block diagram of the proposed system. In order to determined the feasibility of this experiment i begin by activating the accelerometer on my android phone and demonstrate the following activities. "Standing", "Walking", "Football", "Climbing" and "Tram Ride".

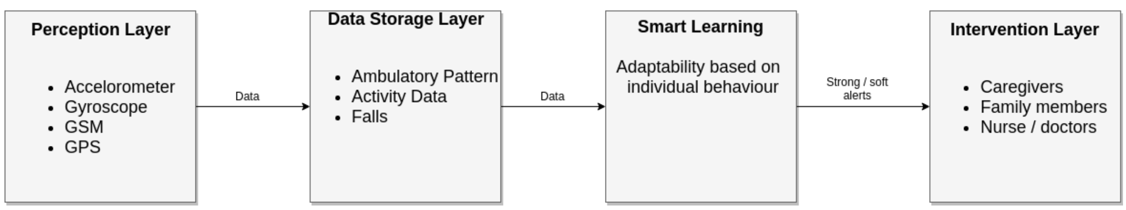


Figure 1: Image Show the block diagram of our approach.

4.1 Perception Layer:

This layer represent the genesis of the whole system, it comprises of accelerometer, GSM, GPS and gyroscope, Accelerometry provide detailed information on physical activities and inactivity and this information can be used to measure more comprehensive relationships among movement frequency, intensity and duration, it can also measure vibration intensity. GSM and GPS is used to monitored the location of the user in case of emergency while the gyroscope will be used to measure orientation in addition to that it also aid to put the accelerometer to sleep when the cane is on pause mode and activate it when pick up again, data gathered by the cane will stored in the storage layer for analysis, Fig 2(a) shows the image of the cane and the attached devices, while 2(b) shows a volunteer simulating some movements with the device.

(a) Cane with devices attached

(b) Volunteer simulating elderly activity

Figure 2: Image (a) show the cane with attached device, Image (b) Shows a volunteer simulating movements.

4.2 Storage layer:

Data generated by the perception layer will be stored here and preliminary process like filtering and feature extraction will be done here before transferred to the smart learning platform which will learn and classify each different activity.

4.2.1 Ambulatory Pattern data:

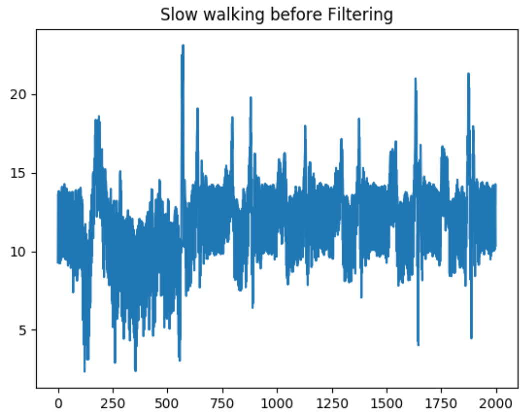
Walking pattern will be collected and stored here this will include but not limited to slow ambulation, extreme slowness in walking, walking and stopping which might be as a results of tiredness, arm shaking and vibrations, adequate learning of this pattern will be useful for the prediction of impeding ailments of the user's.

4.3 Filtering and Noise Removal:

Filtering and noise elimination is a fundamental part of this work; noise may interfere and corrupt the final results. A low pass filter is used here due to its efficiency in removing small amount of high frequency noise and computation simplicity, it passes low-frequency and reduces the amplitude of frequencies higher than the cutoff frequency, Fig 3(a) and (b) shows the signal before and after Filtering with low-pass.

$$y_{(i)} = \sum_{i=1}^{n} y_i - 1 * \alpha(x_i - y_i)$$

$$0 < \alpha < 1.$$



(a) Signal before Filtering

(b) Signal After Filtering

Figure 3: Image (a) show the raw Signal Before Low Pass Filtering, Image (b) Shows Signal After Filtering.

4.4 Feature Extraction:

Signal Magnitude Area (SMA) can be used as a measure for differentiating between static and dynamic activities with the use of all three axis in the accelerometer signals, we achieve this by computing the sum of vector magnitudes of the three axes.

$$SMA = \sum_{i=1}^{n} (|X_{(i)}|) + (|Y_{(i)}|) + (|Z_{(i)}|)$$

Energy Feature: The set of feature extracted here are use to discriminate between different types of activities such as walking, pausing, shaking, and can also used to identify the rate of velocity during ambulation such as fast walking, slow walking and extreme slowness in ambulation, we compute the short time Fourier transform (STFT) using the energy absorption.

$$X_i[k] = \sum_{n=-\frac{N}{2}}^{\frac{N}{2-1}} w[n]X[n+lH]e^{-j2\pi\frac{kn}{N}}$$

$$w = analysis\ window$$

$$l = frame\ number$$

$$H = hop - Size$$

4.5 Smart Learning Platform

This will be an incessant learning environment which can be learn based on individual daily ambulatory activities and if abnormal activities are detected a soft or strong alert will be activated and the intervention layers will be notified accordingly, a soft alert is activated if some unusual activities (but regarded as a learn't norm for the said individual) is detected for example a person who frequently drop the cane and pick it up again within the stipulated time frame. A strong alert is activated if the behavior is completely alien to the individual.

Our approach has so many advantages over all other existing methods, first the non-intrusive nature of this method, users don't need to wear any special bracelet or wrist monitoring, they only to pick up the cane when they need to ambulate which acts as the traditional and the usual aids for the old, weak and disable people right from time immemorial and the simplicity and adaptability to the user behavior which can be learned in both supervised and unsupervised ways.

4.6 Classification using LDA

Linear Discriminant Analysis (LDA) is mainly commonly used as a dimensionality reduction procedure in the pre-processing step for pattern-classification and machine learning applications. The objective is to project a dataset onto a lower-dimensional space with good class-separability in order avoid overfitting ("curse of dimensionality") and also reduce computational costs. LDA is a second order statistical approach and a supervised classification approach that utilizes the class specific information maximizing the ratio $j_{(w)}$ of the within and between class.Fig 4 and 5 Show the results of activity classification with linear discriminant analysis, (fig 5 shows the test set highlighted).

$$j_{(w)} = \frac{w^T S_b w}{w^T S_w w}$$

where S_b and S_w are the between and the withing class respectively, they are computed as follow:

$$S_b = \sum_{k=1}^{k} (m_k - m) N_k (m_k - m)^T$$

$$S_w = \sum_{k=1}^{k} \sum_{n=1}^{N_k} (X_n k - m_k)(X_n k - m_k)^T$$

N_k is the number of example in k-class and $X_n k$ is the nth data in kth class m is the mean of the entire set and m_k is the mean kth class, Note that we can compute the Langrangian Dual and KKT by maximizing j then we have

$$S_w^{-1} S_b w = \lambda w$$

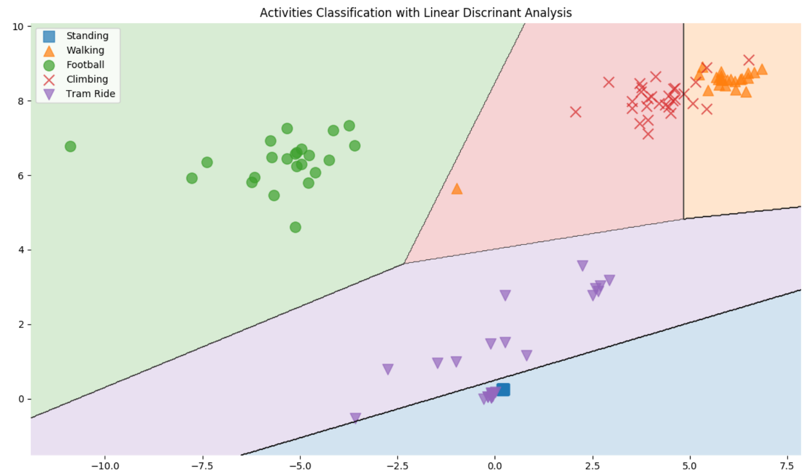


Figure 4: Show Linear Discriminant Analysis

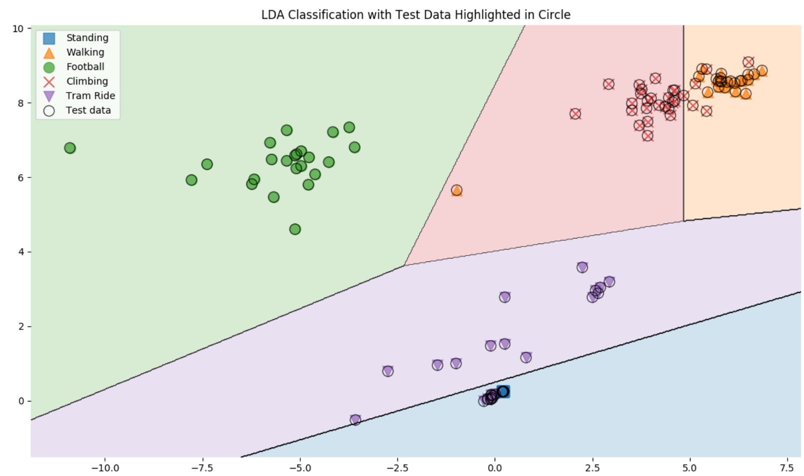


Figure 5: Shows Linear Discriminant Analysis With test data highlighted).

4.7 Dimension reduction with PCA

Selecting the best feature and reducing the dimensionality to forestall the possibility of overfitting is a very important aspect of learning, principal component analysis (PCA) is a very popular and effective method for achieving dimension reduction, in addition to this, PCA can help in speeding up the learning rate of a classifier. I subject the data to PCA and the results is a better classification of our data.

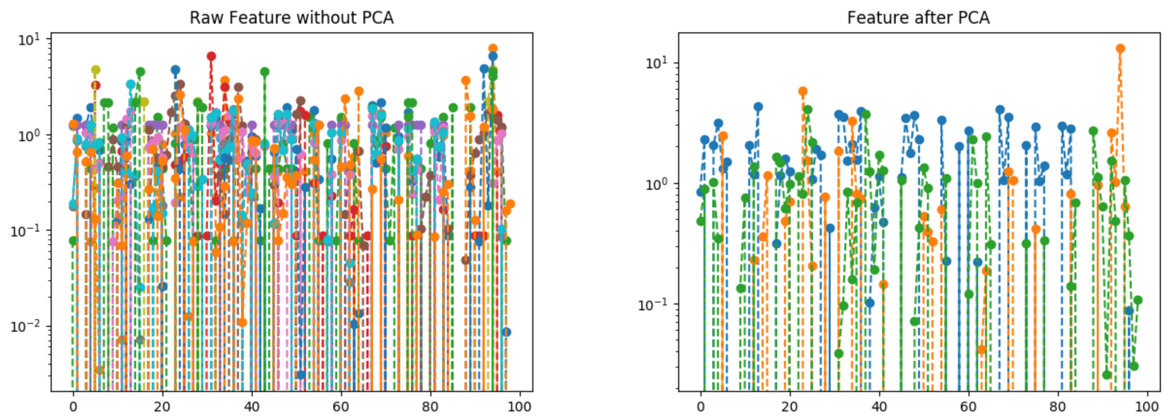
PCA work by finding maximum variance for the whole data although for PCA to be efficient we need to first scale the feature in our dataset by setting the mean to zero and variance in to one known as standardization technique and it's the property of a normal distribution. Using PCA for feature selection is completely un-supervised and it's done by preserving the standard variation. Consequently we combine similar feature together and create a more meaningful and orthogonal superior attribute and this time in a lower dimension with no redundant information. Fig 6 (a) and (b) shows the raw data without PCA and the resulting data visualization after applying PCA respectively, while Fig 7 shows a better classification with LDA after applying PCA to the data.

Lets x be a vector of random variable r such that transpose of x is denoted by x^T therefore, we can have $x = [x_1, x_2, ...x_r]^T$

Now we need to find the a linear function of x that can maximize the variance $\alpha_1^T x$ where α_1 is a vector of r constant $\alpha_{11}, \alpha_{12}, ...\alpha_{1r}$, and $\alpha_1^T x$ become

$$\alpha_1^T x = \alpha_{11}x_1 + \alpha_{12}x_2, ... + ... + \alpha_{11}x_r = \sum_{j=1}^{r} \alpha_{1j}xj$$

.



(a) Feature Space without PCA

(b) Feature Space after PCA

Figure 6: Image (a) show the feature space without correlation this might be mis-leading for any classifier, image (b) Shows PCA combine similar feature together and create a more meaningful and orthogonal superior attribute.

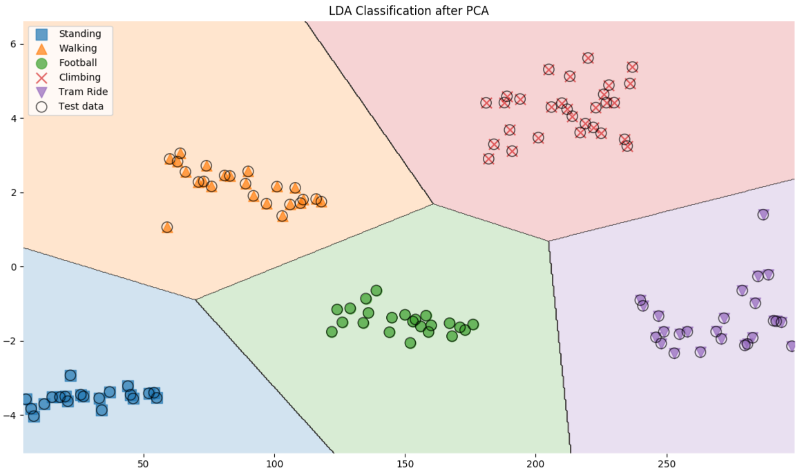


Figure 7: Shows Better Classification after dimension reduction with PCA.

4.7.1 LDA Observation

It can be observe that we are able to successfully classified different activities using linear discriminant analysis, Fig (4) and (5) above shows the classification without reducing the dimension (Note some misclassification between "Standing" and "Tram ride" also misclassification between "Walking" and "Climbing"), and Fig (7) shows a better classification after subjecting the data to PCA before classification, this prove the importance of dimensionality reduction before classification.

5 Anomaly Detection and Data analysis

Part of the objective of this study is to detect anomaly related to the elderly ambulation,the smart cane was activated and data collected for analysis more-so, since data is an integral part of this studies and accurate data collection is required to guarantee the integrity and cohesion of this device, therefore,in the absence of the real data from the actual end user, ambulation data with step count were gathered by demonstrating and mimicking the movement of the elderly, subsequently feature engineering and analysis was carried out on the said data, the following data were gathered from the cane.

Activities Data: is a set activities that are trigger when the user takes the cane, and it stop when the user put the cane down, data in this categories include

- Activity begin time
- Activity end time
- Number of steps

Pauses: this is sub-activity that happen when no step has been detected for 15 seconds, it automatically stops when a step is detected data in this categories include

- Pause begin time
- Pause end time

Alerts: this may be trigged by the occurrence of accidental fall when this occur the cane vibrates and the user has up to 15 seconds to cancel it by picking it up else it will be reported as fall, data in this categories include

- Fall time
- Fall alert(false when cancel otherwise true)

5.1 Data description

Data description and documentation is necessary to ensure that the researcher, and others who may need to use the data can make sense of the data and understand the processes that have been followed in the collection, processing, and analysis of the data, below are the description of each column and how they are computed.

- **Date:** This represent the day column and the day the activity was carried out
- **Step count:** The total number of steps taken by the user on a particular day.
- **Pause duration:** The total duration of pause by the user during activity its represented in seconds

- **Mood:** This is an heuristic feature that intend to express the user's feeling on a particular day although this is assume not to be 100 percent accurate but might be interesting to estimate user's daily mood and its computed based on the following algorithm, it turns out that an average person has a step of approximately 2.1 to 2.5 feet. therefore it takes approximately 2,200 steps to walk one mile, and a step of 1000 will cover about 762 meters, so if an aged person (who is mentally stable) can take about 3000 step on a particular day which is more than 1 mile walk then he/she is assumed to be in a great shape and excellent mood.

```
walk_duration = []
for i in range(0,len(walk_duration)):
if walk_duration >= 3000:
mood is 'Excelent Mood'
elif walk_duration >= 1000:
mood is 'Very good mood'
else:
mood is 'moody'
```

  Mood is represented in binary as follow, 100 = moody, 200 = Very good mood and 300 = Excellent Mood.

- **Activity begin:** This is the beginning of a daily activity literately when the cane is picked up.

- **Activity end:** This is the end of a daily activity literately when the cane is finally laid to rest and no activation is detected for the rest of the day.

- **Activity length:** This is the length of total activity for the day, it is computed from the sum of the difference of the activity begin and activity end time and converted in to second.

- **True falls:** A true falls is detected when the cane loose its equilibrium and balance is not regain in 15 seconds interval.

- **Walk duration:** This can be referred to as total active moments of the day because it represent total duration of ambulation by the user, its computed by taking the sum of walking duration minus total pause duration.

- **Tiredness:** This is the rate of exhaustion that maybe experience by the user, tiredness maybe due to fatigue or sign of physical weakness that can be experience as one grow older or it can signify sign of distress, it is computed by taking the ratio of pause duration to the walk duration, it maybe noted that threshold can be set for this and a distress alert can be generated if tiredness is greater than 1 this is definitely not a good sign because it means the user pause more often than doing the actual walking, although it may not be 100 percent accurate because user may pause to talk to people or due to some other reasons.

- **Speed:** This is the rate of change of distance of the user, we can estimate how fast the user move and this is computed by taking the ratio step counts to walk duration.

- **False falls:** This is a trigger alert when the cane loss its equilibrium but cancel by been pick up withing the 15 seconds time frame.

- **True fall time:** This is the time when true falls occur.

- **False fall time:** This is the time when false falls occur.

5.2 Anomaly Detection with Isolation forest

After the feature engineering task its time to classify our data and try to detect anomalies. Isolation forest is a relatively new algorithm but becoming more and more popular due to its simplicity and efficient usage of memory, the algorithm is based on the fact that anomalies are data points that are the minority and unusual and therefore they can be secluded. This technique is a little bit different from traditional way of isolating anomalies which are mostly based on distance to their neighbor and sometimes density difference, one big advantage of this method is the computation efficiency and its low memory usage, the algorithm has linear time complexity which make it suitable if we decide to implement it directly on the cane.

The Isolation Forest algorithm isolates observations by randomly selecting an attribute and then randomly selecting a split value between the upper limit and lower limit of the selected attribute. Then by comparing an observation based on the different an anomaly can be easily spotted but isolating normal observations require more conditions. Isolation is done by creating isolation trees, or random decision trees, the number of splitting required to isolate a sample is equivalent to the path length from the root node to the terminating node. Then, the score is calculated as the path length to isolate the observation, finally when a forest of random trees collectively produce shorter path lengths or particular samples, they are highly likely to be anomalies. Fig 8 and 9 shows anomaly detection with I-forest (fig 9 detect anomaly in a completely new test set)

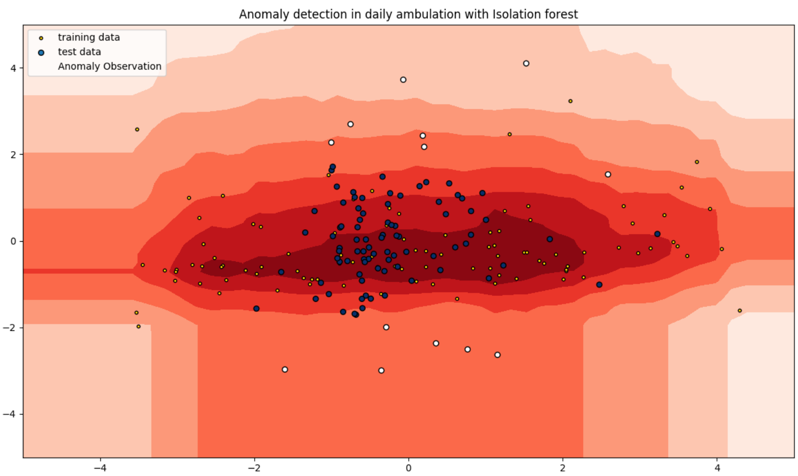


Figure 8: Anomaly Detection with I-forest

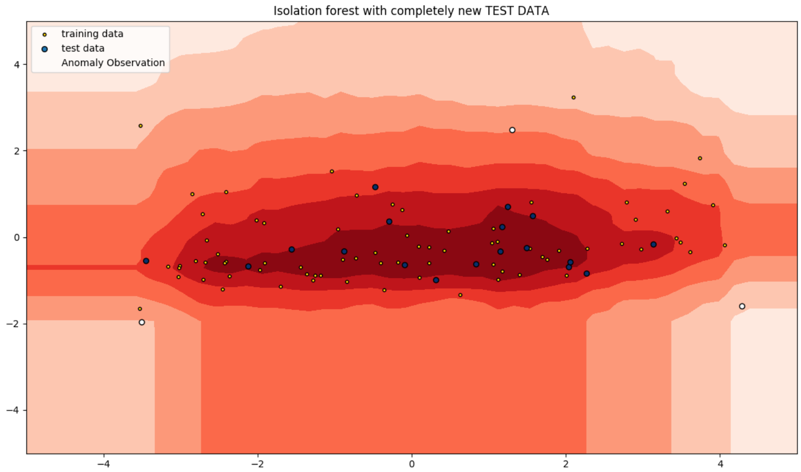


Figure 9: Shows I-forest with new test-data (note the anomaly in white).

5.3 Anomaly Detection with One-Class SVM

Another algorithm evaluated on our data is One-Class SVM, this is a special case of Support Vector Machine that learn a hyper plane by separating all the data points from the basis and constructs a smooth boundary around the majority of probability mass of data, it is an unsupervised algorithm that learns a decision function for uniqueness detection by classifying new data as similar or dissimilar to the training set which makes it suitable for detecting anomaly.

given a data-set X, with an unknown label, and a $\Phi(X)$ RKHS map (kernel Hilbert space) function from the input space to the feature space F, a decision function $f(X_n)$ in the feature space F is given as $f(X_n) = w^T\Phi(X_n) - r$, to separate as many as possible of the mapped vectors $\Phi(Xn :), n : 1, 2, ..., N$ from the origin. Where w is the norm perpendicular to the hyper-plane and r represent the bias of the hyper-plane, then we arrive at:

$$min_{(w,r)}\frac{1}{2}\|w\|_2^2 + \frac{1}{v}.\frac{1}{N}\sum_{i=1}^{n} max(0, r - \langle w, \Phi(X_n :)\rangle) - r$$

v is the is the parameter that represent the balance between maximizing the hyper-plane and the total data-point permitted across the boundary and v ranges between (0, 1). Fig 10 and 11 shows anomaly detection with One-class SVM (fig 11 detect anomaly in a completely new test set)

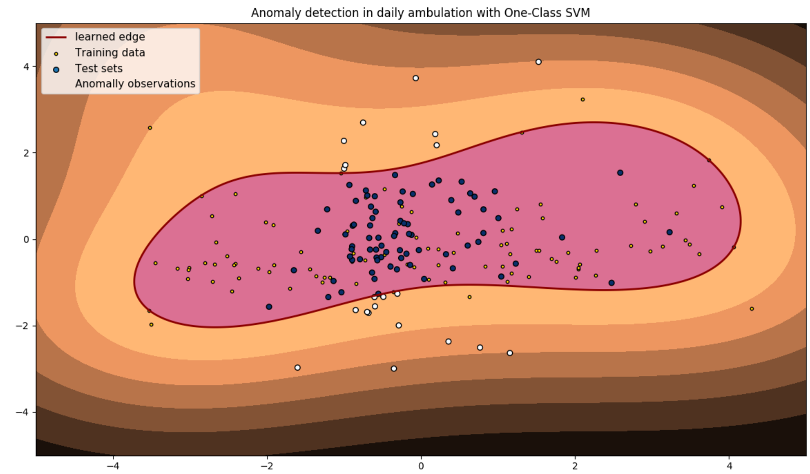


Figure 10: Anomaly Detection with One-Class SVM

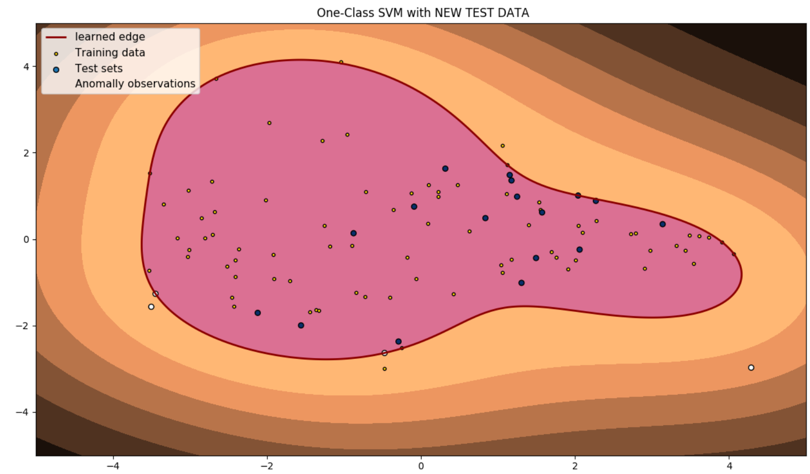


Figure 11: Shows One-Class SVM with new test-data (note the anomaly in white).

6 Detecting diseases associated to ambulation

Now that we are able to detect and isolate anomaly related to ambulation i still think we can do more exploration by trying to effect the possibility of detecting diseases associated to ambulation that are common with the older people, i started by looking at some common diseases with related symptom and their association with ambulation which mainly resulted in Inability to walk.

Inability to walk without hindrance also known as gait abnormality is one of the major sign of aging , this form of anomaly has been categorized as one of five types based on the symptoms or appearance of an individual's walk [24]. They are spastic gate, scissors gait, step-page gait, waddling gait and propulsive gait. Studying these gait abnormality is imperative part of diagnosis that may afford us the required information about this neurological conditions. Gait abnormality may be due to musculoskeletal weakness, injury or genetic factors, on the other hand abnormal gait can also be the results of attack on the nervous system by diseases, some of the common diseases associated to abnormal gaits are.

6.1 Apraxia

Apraxia is a neurological condition characterized by loss of the ability to perform activities that a person is physically able and willing to perform or the loss of ability to properly use the lower limbs in the act of walking, this is a walking disorders found in a subgroup of patients with Alzheimer's disease [25]. Patients walk with slow and irregular steps and find it hard to negotiate turns, climb onto a stepping stool and most time they exhibit hesitating steps during movements, sometimes patients may find it difficult to speak or move arms or legs completely.

6.2 Parkinson

Parkinson and Apraxia are closely related in symptom, Patients with frontal gait disorder at first look as though they have a parkinsonian gait, [26] with short, shuffling steps, poor balance, initiation failure, and hesitations on turns, the most glaring symptoms associated to Parkinson is shaking , Trembling in fingers, hands and arms. In this gait, the patient will have rigidity and bradykinesia [26]. He or she will be deformed with the head and neck forward, with flexion at the knees. The whole upper extremity is also in flexion with the fingers usually extended. The patient walks with slow little steps known at marche a petits pas (walk of little steps). Patient may also have difficulty initiating steps. The patient may show an involuntary inclination to take accelerating steps, known as festination. This gait is seen in Parkinson's disease or any other condition causing Parkinsonism.

6.3 Alzheimer

This is another neurological disease that can be very devastating; the patient suffers from memory loss and may have trouble with comprehension of his or her environments which often lead to an un-necessary wandering in the neighborhood; gait apraxia might be developed in a long run and generally patients with Alzheimer's disease are at increased risk of losing their balance [29]. although the major symptom of this disease is memory loss but most patients at the early stage may have show a sign of abnormality in gait and maybe misdiagnose as apraxia, presently there's no effective cure of Alzheimer but early diagnosis can be very useful especially when gait abnormality is detected.

6.4 Arthritis

This disease conditions affect joints, including lupus and rheumatoid, the symptom might include fatigue, joint pain and general abnormality gait behavior, although arthritis is a very popular disease but not well understood because it might be the results or combination of several other diseases. Severe arthritis can result in chronic pain, inability to do daily activities and make it difficult to walk or climb stairs [27]. Arthritis can cause permanent joint changes and generally impaired ones ability to ambulate freely.

6.5 Learning Ambulation Pattern

Nutt et all [28] gave two conditions or abilities that are required for walking equilibrium, the capacity to assume the upright posture and maintain balance; and locomotion;the ability to initiate and to maintain rhythmic stepping. These two conditions are separate but interrelated components of gait and when one or both of this condition is lacking then we can rightly conclude that the individual might be suffering from walking abnormality, detecting diseases related to gait abnormality with smart-cane might look trivial at first, but when we realize the facts that cane or walking stick has been used as an assistive device to aid in ambulating especially in the elderly and disable right from the time immemorial then embedding smart devices (that can learn ambulating pattern and detect anomaly associated to it) in to cane or other walking aids will help in early detection of this diseases and greatly reduced over dependent of the patients on caregivers.

6.5.1 Common Symptoms:

Akinesia or slowness in ambulation is the symptom of most of the disease mention above, generally they often result in difficulty in movements, this difficulty is particularly noticeable in complex movements such as walking, patients are affected differently depending on the degree of the illness, using assistive devices such as canes, crouches and walker is a standard requirements for people suffering from abnormal gait diseases and the facts is if we can adequately learn the pattern of ambulation of an individual we could detect the likelihood of this disease before getting to advanced stage and make adequate recommendation for the patient to visit a physician.

6.5.2 Data Gathering and Pre-processing

The cane was activated again and different movement was simulated by different individual who mimic the symptom of each disease. Some of the action recorded are slow walking, extreme slowness in walking, walking and intermittent pausing which might be as a results of tiredness, arm shaking and vibrations and aimlessly walking(zig-zag movements) all this data were gathered and preprocessing was done like section (3) above, then since each activity is label we try to classify different activity with linear discriminant analysis again. Fig 12 shows behavior classifications with LDA

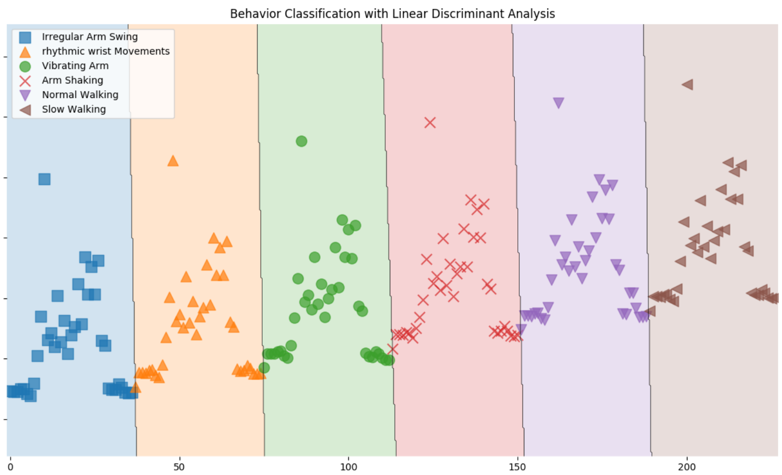


Figure 12: Behavior Detection with LDA

7 Conclusion

Findings of this study indicate that its quite feasible to detect anomaly in the elderly ambulation behavior and can be applied to aged care system, the smart cane approach has so many advantages over all other existing methods, first the non-intrusive nature of this method and also the facts that cane has been used as an ambulatory aids for the old, weak and disable people right from time immemorial and the simplicity and adaptability to the user behavior which can be learned in both supervised and unsupervised ways.

We demonstrated the application of simple and computational efficient algorithm such as LDA to detect and learn behavior which may lead us to detect tremor by learning the pattern of ambulation of a user and the possibility of detecting the likelihood of disease before getting to advanced stage and make adequate recommendation for the patient to visit a physician, ambulatory pattern like slow ambulation, extreme slowness in walking, walking and stopping (which might be as a results of tiredness) arm shaking and arm vibration were successfully learn and classified.

We also demonstrated the simplicity and efficient usage of this technique since based on our knowledge there's not known technique that has explore the use of smart cane been proposed here to detect anomalies in ADL based on ambulation , ambulatory anomaly were learn and isolated with the usage of Isolation forest and One class SVM, falls are easily and naturally detected with the cane and different mode of alert (soft and strong) technique for the intervention system are proposed to forestall and limit the possibility of type 2 error.

7.1 Future evolvements and way forward

Accurate disease prediction actually take some time and the success rate will also depend on more data, i will suggest we take a subset of sample (users) to train our algorithm on, we will also need to enhanced the cane with more storage ability to be able to gather some weekly data based on pattern, also we will need medical expert assistance to gathered different existing pattern to train our algorithm. Its very imperative to note that algorithm get better and better with more data, therefore i recommend we gathered real data from the end users(elderly people) and subject both algorithm in to test, we should adopt at least a weekly training of this algorithm with our real data and observe how they adapt based on the training and prediction.

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