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Proje Yürütücüsü:
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Önsöz

Wearable devices are penetrating everyday life of allowing an ever increasing collection of personal data. With support by TUBITAK this project builds know-how on processing personal data and its use.

İçindekiler

Tablo ve şekil listeleri

Özet

Akıllı giysiler, giydirilebilir sensörler ve benzeri küçük cihazlar askeri, sağlık ve kişisel uygulamaların geliştirilmesinde çok değerli geri bildirimler sağlar. Bu bildirimler, toplanan bilgilerin basit kullanımlarının ötesinde, istenmeyen sonuçlarda çıkarılabilir. Temel konular insanlar olduğunda, bu tür çıkarımlar, bireylerin yasal gizliliğiyle beklenen ve korunanları kolayca ihlal edebilir.

Bu tür veri analizi hakkında bir fikir edinmek için projemiz yürüyüş verileri ve yer gizliliği konusunda seçildi. Yürüme verileri genellikle koşma, yürüme, merdiven çıkma, düşme gibi aktivite tanımlama veya osteoartrit gibi tıbbi durumların izlenmesi ile ilgilidir. Buna rağmen; bireylerin günlük fiziksel aktivitelerini (adım sayısı vb.) izlemek için çeşitli mobil uygulama formunda çeşitli kişisel asistanlar var. Tartıştığımız bu veriler, küresel konumlandırma (GPS) verilerine başvurmadan bir bireyin konumunu belirlemek için kullanılabilir. Bu proje bu sorunu ele aldı.

Gönüllü bireyler üzerinden pil ile beslenen IMU sensor ve kablosuz WiFi modüller kullanılarak 3-eksen ivme verileri toplandı. Bu amaçla tasarlanan elektronik devre kişinin her bir ayağı için dizüstü ve dizaltına bölgelerine yerleştirildi (toplam 4 adet). Kablosuz tasarım birden fazla bireyden veri toplamaya izin verdi. Veri toplama işlemi eğimli yolda yukarı çıkma, eğimli yolda aşağı inme, merdiven inme, merdiven çıkma ve düz yolda gerçekleştirildi. Toplanan veriler eğitim, validasyon ve test verisi olarak 3'e ayrıldı. Ayrılan bu veriler ile çeşitli özellikler (ortalama, standart sapma vs.) ortaya çıkarıldı. Bu özelliklerden en verimli olanlarını tespit edebilmek için PCA (Principal Component Analysis) yöntemi kullanıldı. Bu veriler belirlendikten sonra ise kişinin konumunu belirlemek için SVM (Support Vector Machine) algoritması kullanılmaktadır.

Abstract

Smart garments, wearable sensors and similar small devices provide invaluable feedback in development, be it military, health or personal satisfaction. Beyond the straightforward use of collected information one can infer unintended knowledge. When the underlying subjects are people such deductions can easily violate the expected and protected by law privacy of individuals.

To get an insight of what seemingly unrelated information can be extracted our project selected gait data and location privacy. Gait data is usually associated with activity recognition, such as running, walking, climbing stairs, falling; or with monitoring certain medical conditions such as osteoarthritis. However, there are various personal assistants in the form of say mobile applications that keep track of daily physical activity of individuals (such as steps count). Such data we argue can be used to locate the position of an individual without resorting to global positioning (GPS) data. This project takes on that problem.

Using battery powered wireless modules with soldered accelerometers we collected the sensor data in a central processing unit (also battery powered). The wireless modules were attached to human subjects four units per person one below the knee one above the knee on each leg. Data was gathered on different terrains: slope going up and down, stairs going up and down, and level surface. The wireless nature allowed as to collect gait data by more than on subject at a time usually two. During collection the data is recorded based on the terrain the data is gathered and is treated as learning, validation and test data. Extensive amount of data features were extracted and using Pricipal Component Analysis the feature set was narrowed down to a more managable level. Classification of the terrain based on the available data is performed using Support Vector Machines.

1. Introduction

Nowadays, data is becoming ever more important. Tools for processing data are handily available but it is the data that is important. Firms can improve their services, doctors can offer better treatments, researchers can identify new trends and thesis based on data. However, when data is related to humans it can be easily manipulated to extract information about individuals that is either embarrassing or outright violate privacy.

There are various legal attempts to restrict how data is used and shared but attempts so far are lacking, a lot has to do with how privacy is formulated. Understanding and defining all aspects of privacy is non-trivial with many misconceptions, misunderstanding and misuses. Daniel J. Solove article [17] is now a classical work discussing privacy in its most general. This project focuses on location privacy. The widespread availability of wireless phones and networks, free WiFi's, electronic payment systems either implicitly or explicitly provide location data that can be stored and correlated without consent. Andrew J. Blomberg and Peter Eckersley discuss the importance of location privacy in "On Locational Privacy, and How to Avoid Losing it Forever" [3] – report hosted by the Electronic Frontier Foundation.

2. Literature review

Data becomes an ever important commodity. Not long ago Hitachi and East Japan Railways were planning partnership that was to gather and sell travel history of passengers [7]. While GPS devices yield very precise positions, location can be extracted from other sources. Stripping names and addresses is insufficient to protect user privacy. Avoine et.al. [2] claim to be able to identify user of anonymous tickets by collaborating tickets' data with publicly available information. Even anonymous data leaks the location of users. There is an increasing interest in identifying and solving various privacy location issues [8, 5, 14]. As with anything else the solution starts with awareness and understanding of the problem.

Despite their many concerns cell phones and GPS services are invaluable modern tools. Concerns will not stall progress and new tools will be developed. Nowadays wearable sensors are becoming ever more widespread. Their application area ranges from measuring strain in textile [11], to rehabilitation therapy [12], to sports-skills evaluation [20] and many others. Sensors can gather data related to acceleration, force, hearth rate, blood pressure and many others to be used in the such areas.

Our focus is gait analysis. Literature suggests that one of the prime motivations for gait analysis is its application in rehabilitation [6]. As such it is very important that the data collected by such sensors is accurate. Unlike man-made robotic devices where joint movement can be restricted, human joints are prone to deviations and require careful evaluation of sensor placement; see for example [15]. As mentioned in [9, §2.2] obstacles can affect the gait of a person. Naturally external factors such as wind, rain or heat will likely affect a persons gait. In [13] it is suggested that most of gait analysis is focused on straight line walking but sensor data can be used to detect various activities. The current state of the art of smart garments suggests that given gait data such as knee and ankle angles, it is possible to distinguish the type of physical activity a subject performs [4, 10] e.g., climbing versus standing, correlated with publicly available maps such data may leak location data about the user.

We aim investigate the extent of information that raw gait data contains. Rather than focusing on the activity recognition our project deals with terrain classification. There is wide research and data on activity recognition, see for example [18]. Much of the results such as [19] are applicable to this project as well, nevertheless there is the subtle difference that we aim to classify the terrain on which the data is gathered rather than identify the type of activity that is performed.

3. Project proceedings

This project was submitted more that two years ago (10/05/2017), and the various details as discussed later in this text were proposed with the existing technology at that time. Circumstances outside our control resulted in a lengthy delay of the project start day: the project was elected for support on 07/05/2018. Soon thereafter 01/06/2018 the project was initiated.

Sensor technology, wearable devices and microprocessors have a relatively short live with new or updated models emerging frequently. As such the first few weeks were spend on researching existing alternatives to the initial proposal – working with outdated technology would diminish greatly the value of the result and experience obtained from this work. Moreover, fluctuating prices required certain adjustments to the hardware in use.

The first major decision was to switch from wired to a wireless set up. It turned out that the cost of creating wireless devices was sufficiently low that we could stay within a reduced budget while aiming at the same goal. One immediate gain was that we could dispense with PCB design and associated costs. More precisely from Hizmet Alımı (03.5) our budget need not use the allocated 1000TL for creating the physical PCB device (nor one had to be designed). On the other side we had to learn work with wireless technology and amend the type of the devices we purchased under Makine – Teçhizat 06.1 + 06.3.

In our first proposal the first three goals İP1, İP2 and İP3 were modified to meet the change from wired to wireless: there was no need to designing a PCB, instead familiarization with the new hardware was required. We focused on programming and debugging the chosen devices. At this time we requested and were approved to modify our budget not in terms of amount but in terms of purchased hardware. We acquired a mobile projector instead of a laptop to be able to perform more direct and when necessary on the field debugging of the software that was developed.

The move from wired to wireless introduced changes to İP4 as well. At the data collection phase subject were supposed to wear the garment we prepared. Due to hygiene concerns there was a significant reluctance to wear a garment that was worn by another person unless the garment was washed up. Furthermore,size of the garment was a concern. The wireless set up revealed a second advantaged: lack of cables allowed us to attach the sensors to any piece of cloth. Thus every subject could wear their own clothing. It was clear that there is not need to use the remaining funds in Hizmet Alımı (03.5).

There were however unexpected drawbacks. The foremost was that connectivity among the sensors, the wireless modules and the accompanying batteries was fragile. At the initial data collection trials we failed to collect data due power failures attributed to weak links. Consequently, there was need to experiment with different approaches to make the design more robust to environmental factors.

For the remaining of the project on the hardware side we worked mostly on İP5 and İP6. The data that was collected was incomplete and therefore investing any efforts in İP7, İP8 and İP9 as far as categorization and model verification would give unsound conclusions. One aspect that we have not foreseen in our initial proposal was the actual weather conditions. When rain, wind and cold became a regular occurrence collecting data was not possible. Exposing subjects to weather elements during data collection could result in health hazards. Data collection was put on hiatus until spring time. Similar considerations applied to summer when heat prevents prolonged outdoor stays. During the period of no data collection we improved the software by creating interactive control tools to assist field trips and clearing the hurdles that we experienced in earlier field work. Also it was possible to get familiarized with data analysis tools - machine learning and graph theory, see more on graph theory below.

Expecting that we have a short window during which we will be able to collect gait data we started work as soon as possible, both concerning data collection and its analysis. At spring time when weather permitted field data collection was carried out. As a result of the many iteration of design and redesign we did not experience the old problems, but the hardware itself started to fail. Modules broke physically, batteries were at times insufficient, so instead of a laptop computer we spend our budget on acquiring tools that improve the workflow: extra batteries, minor tools, connectors, wireless modules, sensors and the like.

On the data analysis side progress was made but some data appeared inconsistent with expectations. Even though we focused on terrain classifi-cation unlike the literature that is focused on activity recognition there were discrepancies. It was possible that no better classification can be done, but it had to be formally tested. Alternatively, the data we collected was poisoned due to either hardware or software errors. Testing the various venues revealed we had a non-trivial flaw in the way learning data was gathered. The learning data from the various terrains was mixed instead of separated at the collection stage.

Once the issue was identified, the fix was a relatively straightforward matter. We were within the last month of the project but within two weeks we acquired, programmed the necessary devices and gathered new data. In essence we completed İP1 to İP6, and could shifted efforts on the remaining İps.

As for the remaining goals we currently have basic intuition of how the classification algorithm should work. A Masters’ Student is looking at the nailing down the some details of an approach of choice. Independently, I have looked and am looking at certain signal processing techniques that have useful potential.

With another Masters' Student we are developing an algorithm to perform location identification and testing. Details in the next section.

As an overview of the budget changes in Makine – Teçhizat 06.1+06.3, for for the original wire system we have requested

- Kablo soyucu
- Lehim pastası
- Lehim teli
- Multimetre
- Lazer yazıcı
- Disüsü bilgisayar
- 20 adet dişitunik
- 2 adet micro işlemci

The above items were required for the wired device setting. We developed a wireless prototype thus the above hardware was not required. Instead we purchased extra batteries, two tweezers, battery charging devices, wireless modules and peripherals for easing and understand the work with the wireless prototype. As the project initial date was delayed prices have changed so some costs were higher that initially expected but by dispensing with acquiring some of the hardware that was not necessary in the wireless setting we were able to stay within the initial funding limit.

As mentioned earlier the wireless nature allowed us to dispense with Hizmet Alımı (03.5), except for an initial purchase of a test attachment for the sensors to the subject's body.

Next we discuss some technical information and give partial results related to the project.

4. Technical Information and Results

We begin by describing the last method of setting sensors on subjects and present data collected during one of the outing.

Figure 1. Sensor placement

Figure 1 gives a sample view of the final method of placing sensors on subjects. In actual data gathering stage sensors are placed on both legs. The content of the sensor boxes is in the following Figure 2:

Figure 2. Sensor Design

As seen the box contains the sensor (IMU MPU6050) on top of the wireless module (ESP32), within the box are also a charger (bottom left part of Figure 2). The battery is glued to the box cover and not seen in the picture.

Data sets were collected for various terrains with the data acquisition system outlined above. Each data set plotted below consist of x, y, and z values in terms of 'g' of accelerometer. The terrains within the scope of this project are categorized as: level surface, upstairs, downstairs, uphill and downhill. To collect the data set a random sample of student enrolled in Izmir Institute of Technology were asked for assistance, data was also collected by the project members.

Accelerometer data was recorded for various terrains with average effort asked from participants (normal walking). The stairs that were used to climb up were also used when climbing down. Likewise the same hills were used for both uphill data collection and downhill data collection. Below are figures for a subsample of data that was collected. For each terrain the corresponding plot contains four hundred data points. Since frequency is 40Hz this corresponds to about 10 seconds of data collection.

In the following figures (Figure 3 to Figure 12), a sample dataset obtained from volunteers are given.

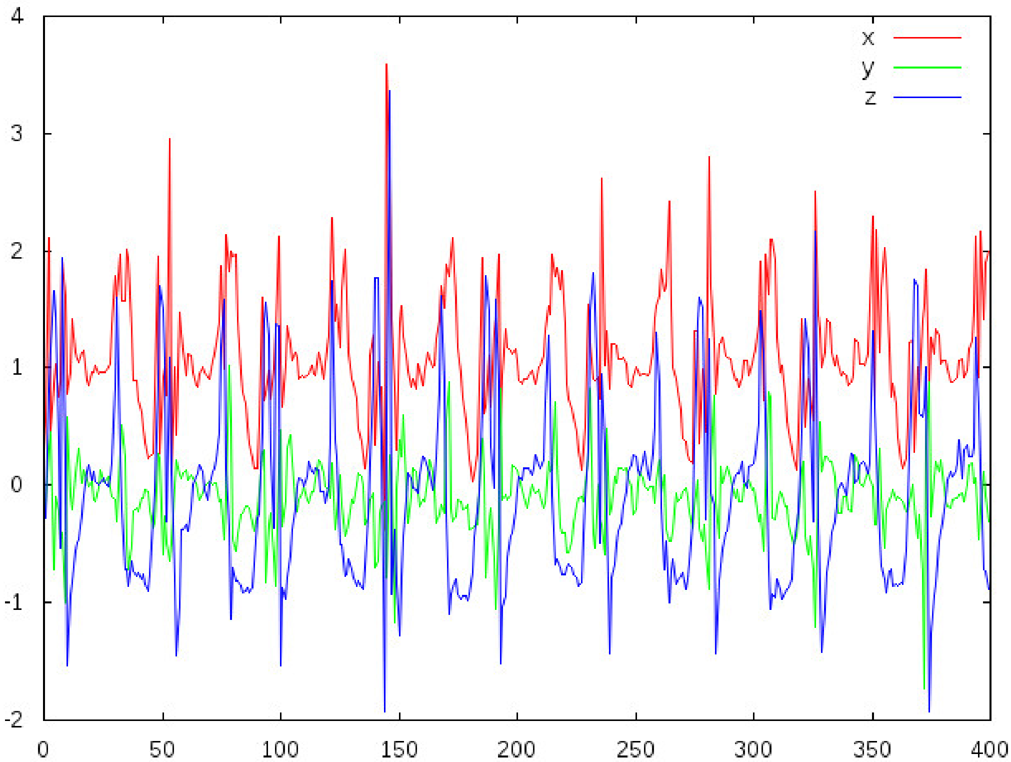

Figure 3. Above knee downhill

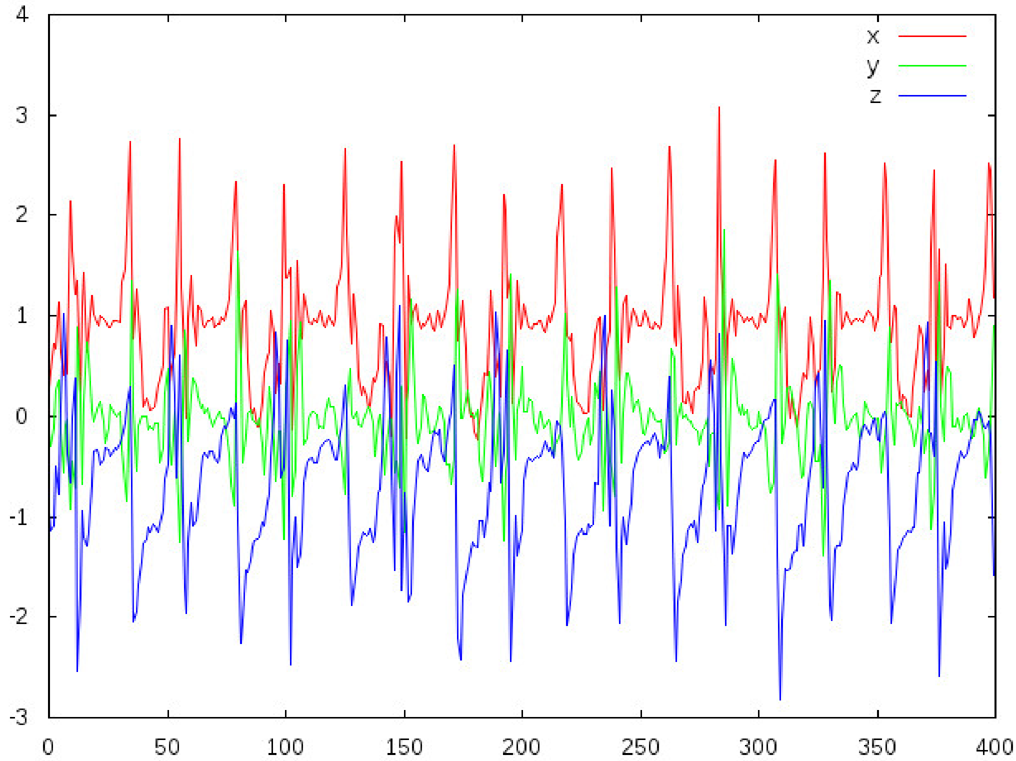

Figure 4. Below knee downhill

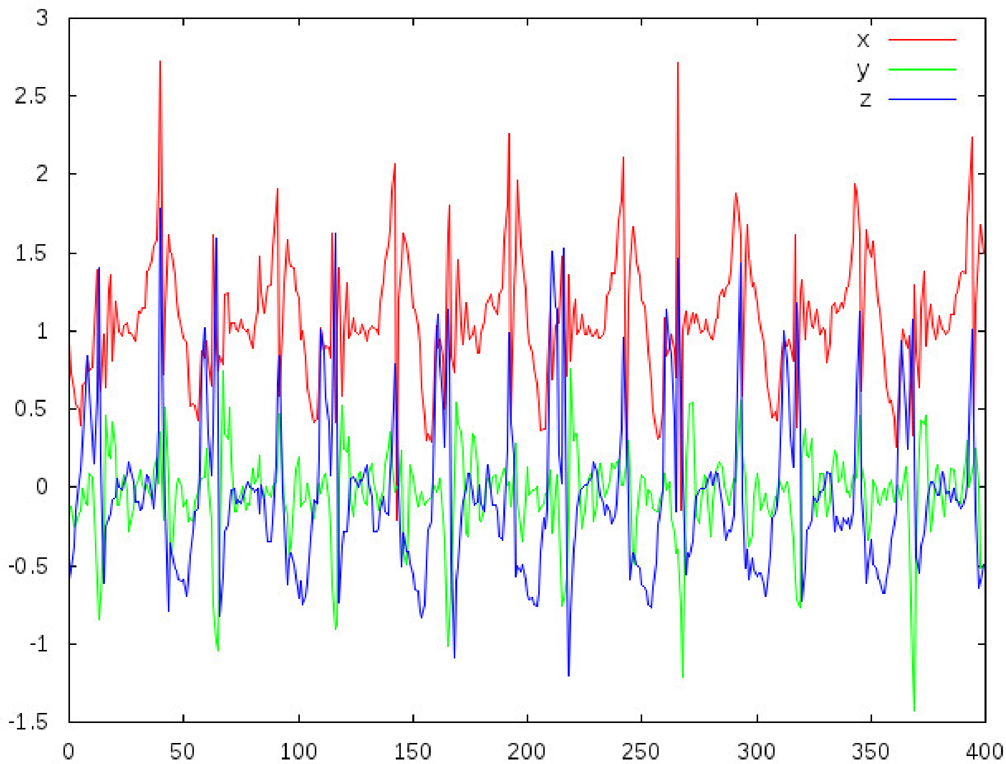

Figure 5. Above knee uphill

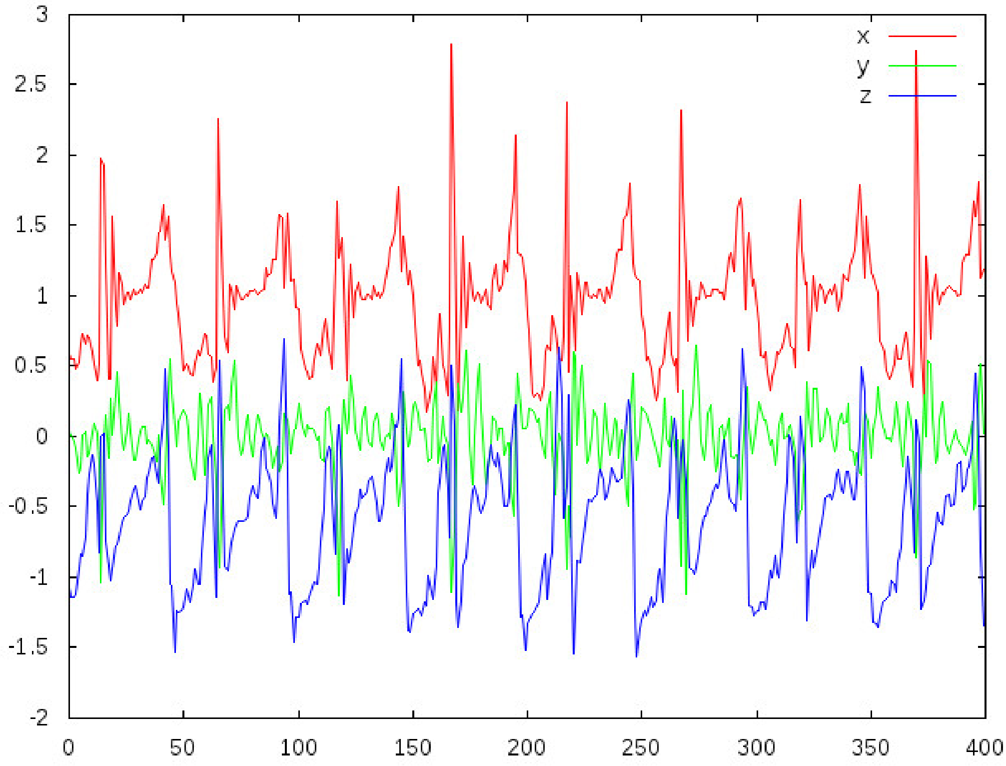

Figure 6. Below knee uphill

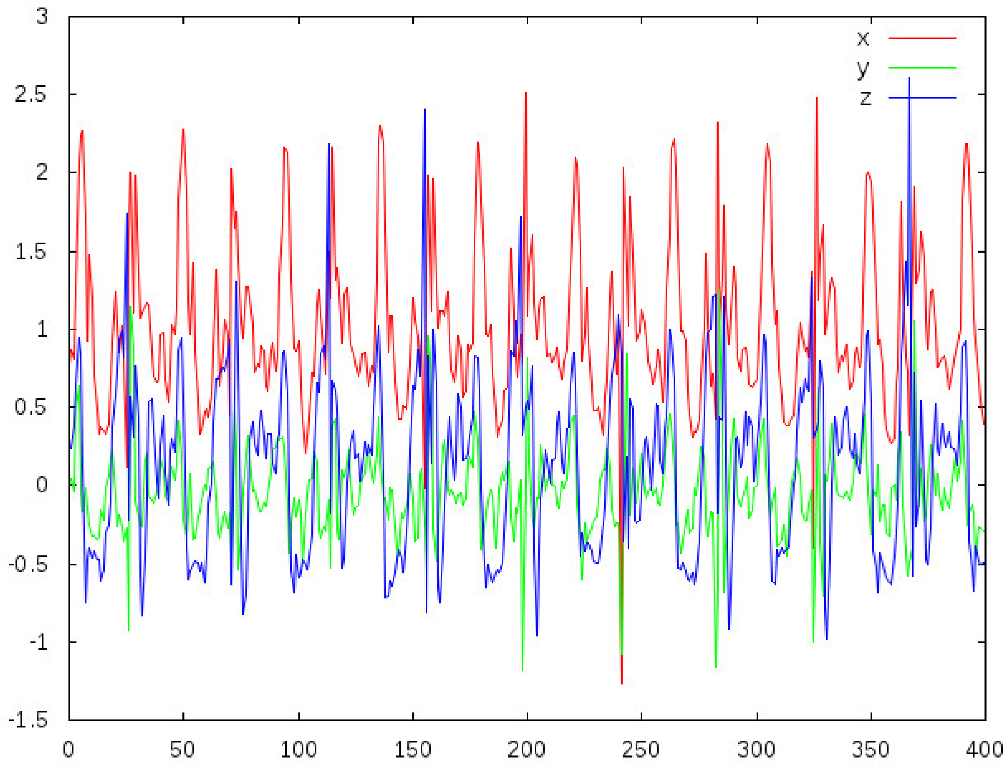

Figure 7. Above knee downstairs

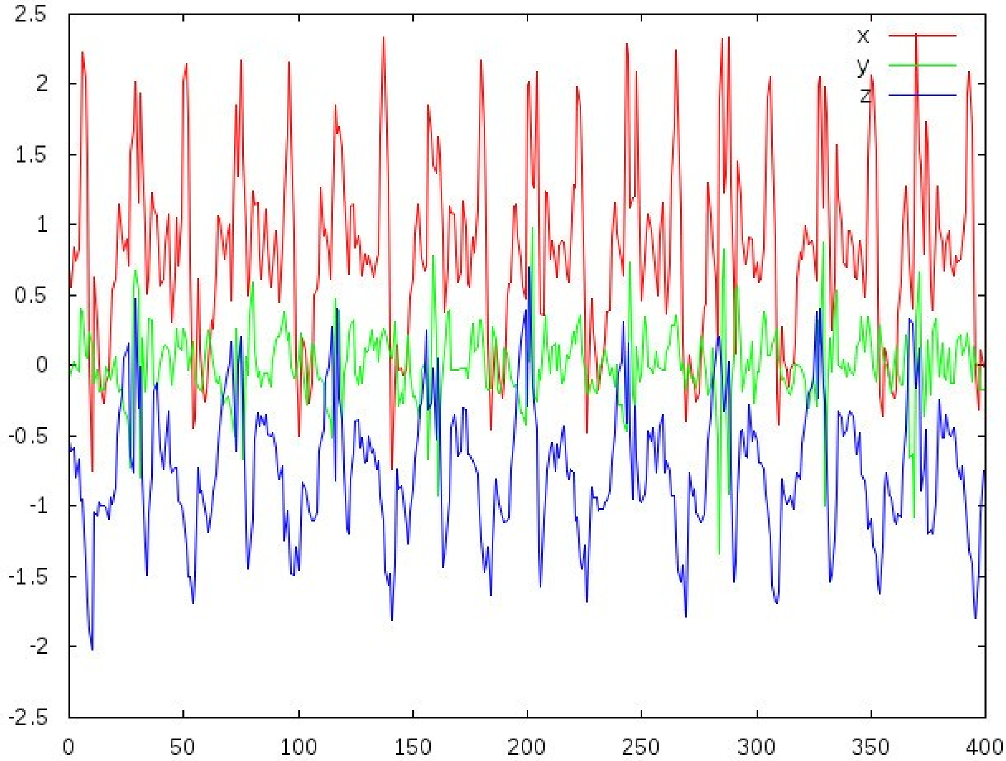

Figure 8. Below knee downstairs

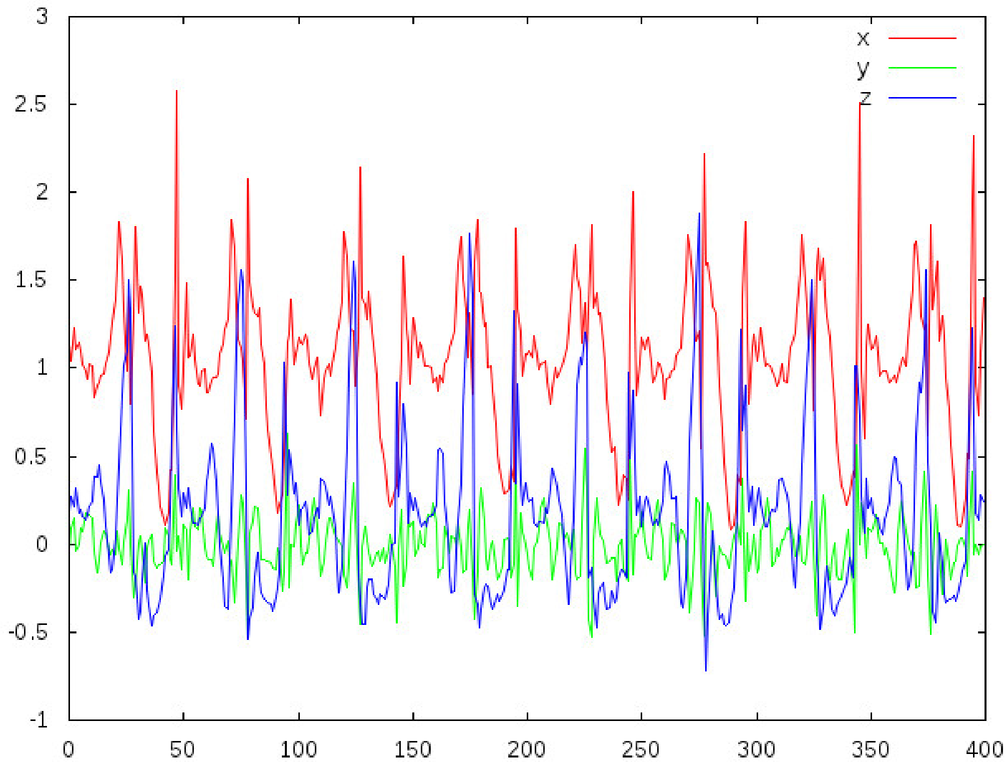

Figure 9. Above knee upstairs

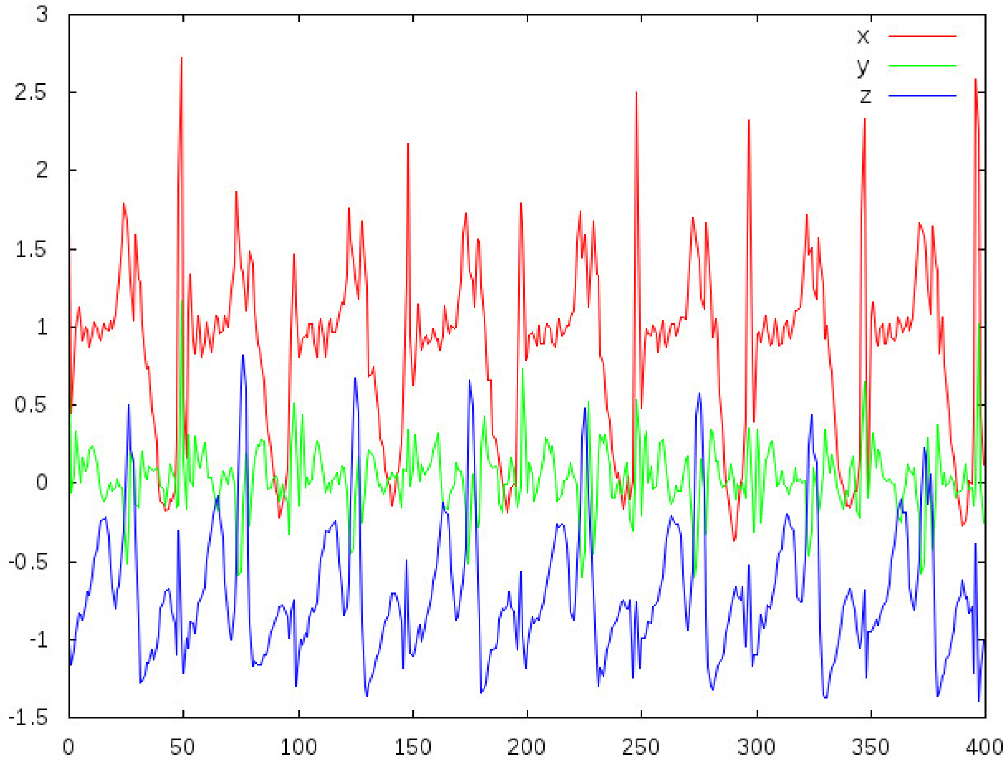

Figure 10. Below knee upstairs

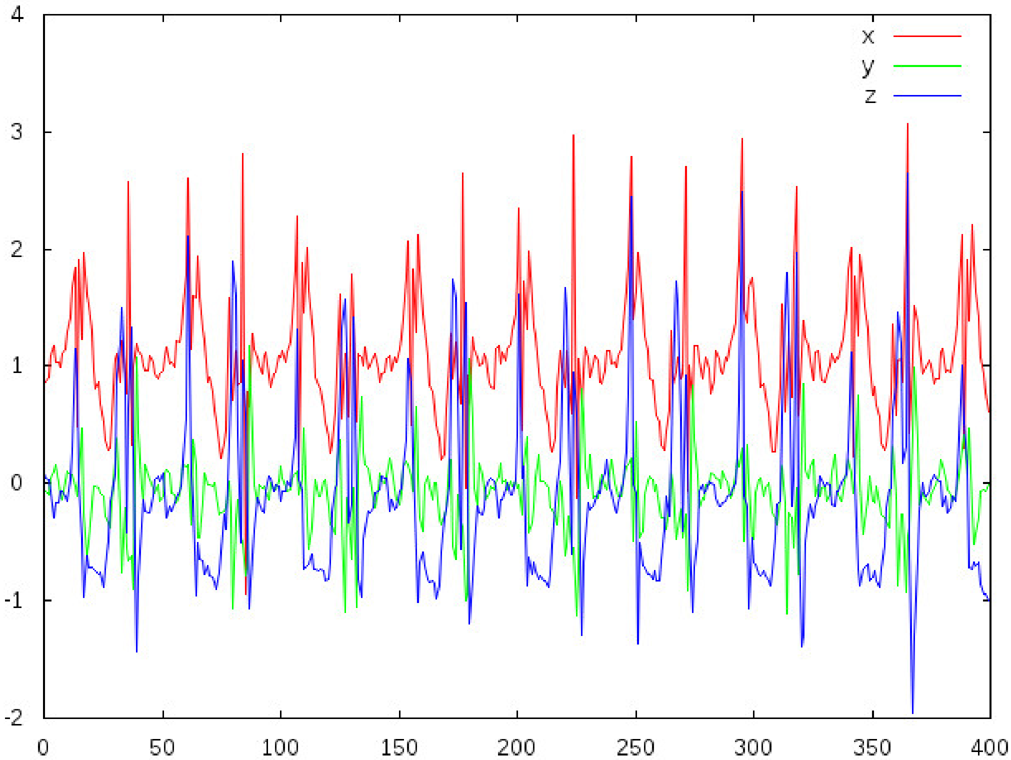

Figure 11. Above knee level surface

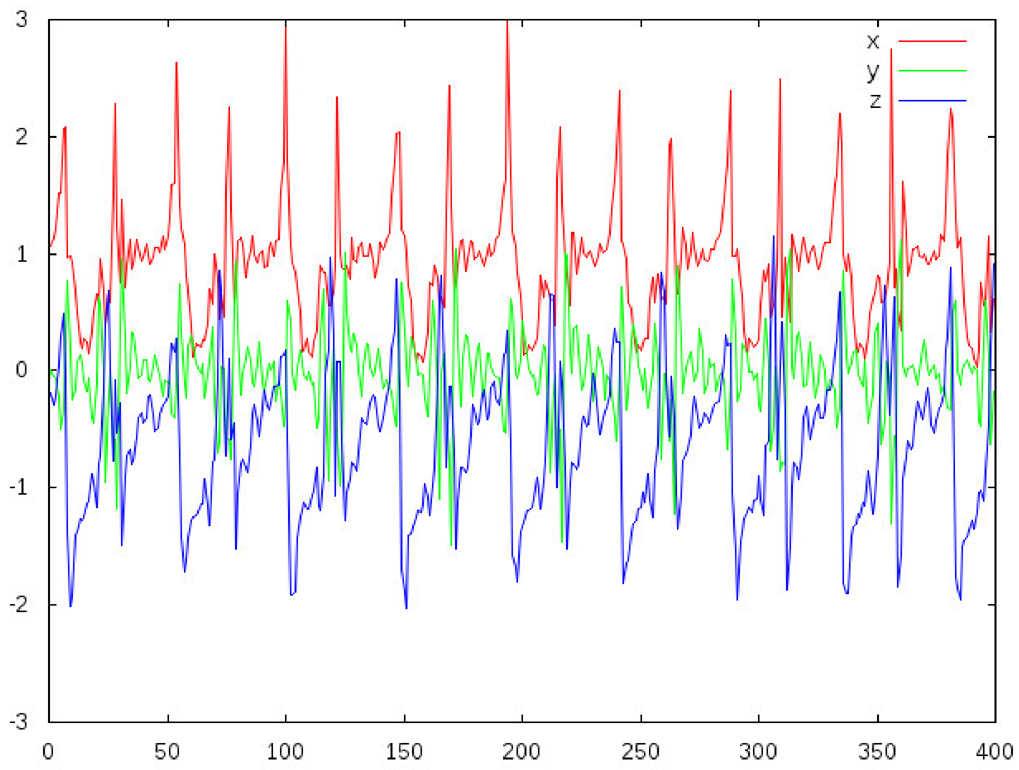

Figure 12. Below knee level surface

To sliding window concept is used to process the data on axes of a walking tour. The window size is set to 50 measurements meaning that each data point has 50 samples (1.25 seconds of walking). The sliding policy is “sliding by half” which means that if a window captures samples 0-50, the following window captures samples 25-75. The intuition behind this half a window overlap is that it preserves the temporality of the data.

Each window’s representative features were selected based on the arguments and discussion in [21]. The description of the features is given in Table 1. The extracted features are concatenated to create the first representation of a window. Despite the seemingly short list in Table 1, the dimension of a vector representing a window is too high. Therefore after transforming these windows into their vector representations the vector dimensions are reduced from 252 components down to 20 components utilizing PCA (Principle Component Analysis). Such reduction speeds the subsequent terrain classification.

Feature	Description
Mean	Averaged signal over the window
Median	N/2th signal of N sized window
Variance	The dispersion of the signals in the window
Averaged Velocity	Integration of the signals on each time t in the window since each point is an acceleration signal.
Averaged Distance	Integration of Velocity function gathered by Integration of the signals.
Zero Crossing Rate	Rate of each signal crossing zero either positive or negative direction. (Could lead to number of steps)
Pairwise Correlation	Correlation between 2 axes of each sensor
Movement Intensity(MI)	Euclidean norm of the total acceleration vector
Averaged MI	Averaged Movement Intensity
Variance of MI	Variance of Movement Intensity

Table 1: Features to represent each window and their descriptions [21]

The classification of these reduced window representation is done via SVM (Support Vector Machines) [16] linear classifiers. Tests on binary pairs of terrains, such as upstairs-downstairs or upstairs-downhill, used five-fold cross validation on the data set. The averaged accuracy of the five-fold is 83.3% between upstairs and downstairs pairs. Tests on other terrain pairs and further classifications is pending the collection of further data that is free from the errors introduced during the initial data collection stages (see previous sections of this report).

5. Outcomes and state of the project

Despite that presently not all İP are fully completed this project will have a significant future impact. Starting the project late required adapting our approach, leading to unforeseen delays. We could not start certain work at the time planned nevertheless we have high confidence in the following:

1. The Electrical Engineering Ph.D. candidate that took part in this project from the beginning will improve his thesis by including the set up into his own research. He will no longer need to work with wired tools, instead his work will use the code from this project with minor changes. It will allow him to extend his work from accelerometers only to any type of sensors

(e.g. force sensors). The experience with field data collection carries out without any change to his project as well.

2. The Computer Engineering student directly supported by this project gains the experience with working with new data not available on the World Wide Web. Having in mind that his work is closely related to Machine Learning the experience of choosing the right parameters and algorithms for a novel data will be invaluable in his own work.
3. The location algorithm that is needed at the final step of this project on its own is problem that is independent of the data we collected. As mentioned above I am working with a Masters' Student in Mathematics whose subject is precisely locating a path with specific properties within a larger graph. We have already established that in certain cases the problem, which we call "edge colored paths" is equivalent the well-known NP-complete "Hamiltonian Path Problem". At the present the student is actively working and planning to finish and defend a thesis within this year. As in the above two achievements TUBITAK's support will be acknowledged.
4. Shortly after completing the data classification and having firmer results on the "edge colored paths" problem, there will be a submission based on the results of this project showing to what extend gait data violates the location privacy of users.

The above items are relatively straightforward outcomes of this project, but the real contribution is the know-how that can be applied to further field projects. Namely

- we can set a wireless sensor network to collect field data;
- we are aware of the various practical hurdles in collecting data with human subjects:
  - means of attaching sensors for minimal physical failure;
  - taking into account weather conditions;
  - better judgement of time requirements to collect data;
- improved debugging and maintenance skills.

6. Conclusion

This project gave us a very good starting point in data collection both in terms of hardware setup and software development. Our initial inexperience resulted in delays but at this stage the remaining parts are a matter of time. We will easi advance this experience in other related research areas with improved costs and time.

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TÜBİTAK
PROJE ÖZET BİLGİ FORMU

Proje Yürütücüsü:	Doç. Dr. BERKANT USTAOĞLU
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Onaylanan Bütçe:	17747.0
Harcanan Bütçe:	13401.33

Öz:	Özet Akıllı giysiler, giydirilebilir sensörler ve benzeri küçük cihazlar askeri, sağlık ve kişisel uygulamaların geliştirilmesinde çok değerli geri bildirimler sağlar. Bu bildirimler, toplanan bilgilerin basit kullanımlarının ötesinde, istenmeyen sonuçlarda çıkarılabilir. Temel konular insanlar olduğunda, bu tür çıkarımlar, bireylerin yasal gizliliğiyle beklenen ve korunanları kolayca ihlal edebilir. Bu tür veri analizi hakkında bir fikir edinmek için projemiz yürüyüş verileri ve yer gizliliği konusunda seçildi. Yürüme verileri genellikle koşma, yürüme, merdiven çıkma, düşme gibi aktivite tanımlama veya osteoartrit gibi tıbbi durumların izlenmesi ile ilgilidir. Buna rağmen; bireylerin günlük fiziksel aktivitelerini (adım sayısı vb.) izlemek için çeşitli mobil uygulama formunda çeşitli kişisel asistanlar var. Tartıştığımız bu veriler, küresel konumlandırma (GPS) verilerine başvurmadan bir bireyin konumunu belirlemek için kullanılabilir. Bu proje bu sorunu ele aldı. Gönüllü bireyler üzerinden pil ile beslenen IMU sensor ve kablosuz WiFi modüller kullanılarak 3-eksen ivme verileri toplandı. Bu amaçla tasarlanan elektronik devre kişinin her bir ayağı için dizüstü ve dizaltına bölgelerine yerleştirildi (toplam 4 adet). Kablosuz tasarım birden fazla bireyden veri toplamaya izin verdi. Veri toplama işlemi eğimli yolda yukarı çıkma, eğimli yolda aşağı inme, merdiven inme, merdiven çıkma ve düz yolda gerçekleştirildi. Toplanan veriler eğitim, validasyon ve test verisi olarak 3'e ayrıldı. Şu aşamada veriler kullanıcı konumunu belirlemek için graf algoritmalarının yanısıra çeşitli makine öğrenmesi algoritmaları ile sınıflandırma için kullanılmaktadır. Abstract Smart garments, wearable sensors and similar small devices provide invaluable feedback in development, be it military, health or personal satisfaction. Beyond the straightforward use of collected information one can infer unintended knowledge. When the underlying subjects are people such deductions can easily violate the expected and protected by law privacy of individuals. To get an insight of what seemingly unrelated information can be extracted our project selected gait data and location privacy. Gait data is usually associated with activity recognition, such as running, walking, climbing stairs, falling; or with monitoring certain medical conditions such as osteoarthritis. However, there are various personal assistants in the form of say mobile applications that keep track of daily physical activity of individuals (such as steps count). Such data we argue can be used to locate the position of an individual without resorting to global positioning (GPS) data. This project takes on that problem. Using battery powered wireless modules with soldered accelerometers we collected the sensor data in a central processing unit (also battery powered). The wireless modules were attached to human subjects four units per person one below the knee one above the knee on each leg. Data was gathered on different terrains: slope going up and down, stairs going up and down, and level surface. The wireless nature allowed as to collect gait data by more than on subject at a time usually two. During collection the data is recorded based on the terrain the data is gathered and is treated as learning, validation and test data. At the current stage we have moved on on developing various Machine Learning algorithms to classify data as well as graph algorithms to deduce user location.
Anahtar Kelimeler:	location privacy, wearable sensors, gait analysis, machine learning, graph algorithms
Fikri Ürün Bildirim Formu Sunuldu Mu?:	Hayır