Irregular Gait Detection using Wearable Sensors

Andreas Lydakis
Computer Science, University of New Hampshire
150 Main St.
Durham, NH, U.S.A.
al1076@cs.unh.edu

Pei-Chun Kao
Physical Therapy, University of Massachusetts Lowell
3 Solomon Way
Lowell, MA, U.S.A.
PeiChun_Kao@uml.edu

Momotaz Begum
Computer Science, University of New Hampshire
150 Main St.
Durham, NH, U.S.A.
mbegum@cs.unh.edu

ABSTRACT

This paper presents a personalized system for detecting irregular gait parameters that may lead to a fall. Accurate detection of gait irregularities may be used to deliver targeted feedback for improving gait patterns and thereby reducing the risk of a fall. The proposed system uses Inertia Measurement Units(IMUs), proximity (PR) and infrared (IR) sensors. We separate the system into two distinct components. The first component is used to detect the current gait phase of the wearer based on the incoming sensor data. The second component combines the sensor data with the label produced by the first component used to classify the gait as regular or irregular in a manner that may potentially lead to a fall. The system can identify the occurrence of three distinct gait irregularities that may lead to a fall: small step width, low foot clearance and excessive trunk sway. For this, we use an Adaptive Neuro-Fuzzy Inference System (ANFIS). The system was trained on three healthy subjects to evaluate its ability to identify irregular gait. Results show that the system can provide real time results with an accuracy equal or greater to similar systems in the existing literature.

CCS Concepts

•**Human-centered computing** → **Human computer interaction (HCI);** •**Computer systems organization** → **Neural networks;** *Robotics;* •**Social and professional topics** → *Assistive technologies; People with disabilities;* •**Computing methodologies** → Anomaly detection;

Keywords

fall detection, fall prevention, gait disabilities, fuzzy systems, ANFIS, motor disabilities

1. INTRODUCTION

Falls are reported as the leading cause of death-causing injury in the elderly population[5], with annual costs of 19 billion US dollars[16]. In addition to medical costs, injuries incur psychological costs that can contribute to depression and antisocial behavior[22]. Because of these reasons, there has been a significant amount of research related to identifying falls and preventing them.

One approach to prevent falls is by introducing physical exercises that improve balance, or increase awareness about fall risks. Depending on a person's physical and cognitive condition, he/she might not be able to follow an exercise regimen. To overcome this limitation researchers have focused on implementing intelligent systems that can analyze human gait patterns and detect imminent falls.

Fall detection systems existing in the current literature vary greatly in methodology and hardware. Use of motion capture and/or camera systems[7] is popular but limited since it cannot be used outside of laboratory settings and without expert supervision. This is why a significant amount of work has looked into using wearable sensors to provide the necessary data in a manner that is unobtrusive and can be used in real world situations. Commonly used wearable sensors include IMUs[21], gyroscopes[17], accelerometers[6], proximity sensors[10], electromyography signals[9] and force sensitive resistors[4].

The human gait cycle can be separated in two main phases, named "swing" and "stance". The two main phases can be separated in different sub-phases as depicted in figure 1. A key aspect of gait analysis for fall prediction is identifying the gait phase[23] . By identifying gait phases a model of the

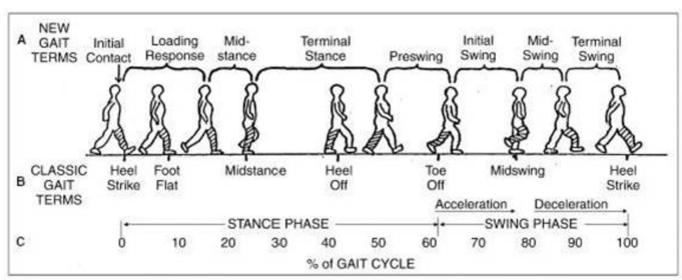

Figure 1: The different phases of the human gait cycle[13].

person's regular gait parameters can be created and used to identify irregularities that may lead to a fall. Accelerometers and gyroscope are widely used for gait phase detection [11]. To address the need of generalization machine learning techniques such as vector analysis[18], support vector machines[3] and fuzzy inference[2] have been used. However, even in those generalized approaches, some parameters

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are hand coded which results in systems targeted at specific subjects.

Gait phase detection has been studied thoroughly in related literature. In[19] the authors use a simple rule based system to detect four different gait phases using a sensor setup similar to the presented system. A more machine-learning oriented approach reported in [23] uses a distributed classifier based on Hidden Markov Models to detect the four phases.

A reliable and systematic way of modeling gait parameters would help to identify gait parameters that may lead to falls and thereby enabling the delivery of corrective feedback for fall prevention.

The proposed system addresses the need for a cost effective and unobtrusive fall prevention system. Although there has been a surge of development in supportive systems such as prostheses (CYBERLEGs project) and exoskeleton-like systems, these solutions are still not ready to be widely deployed. Factors that contribute to this are the high cost of the systems, and the additional weight that the user has to carry in the form of battery packs and mechanical components.

This paper presents a novel system to detect irregularities that may lead to a fall using an ANFIS. Fuzzy logic and ANFIS have been extensively used in human gait studies. For example, the system reported in[2] detects falls using an ANFIS and evaluated it using the Mobifall data set [24]. Using acceleration data in combination with other sensors are a popular approach for fall detection [8, 14]. Using 3D cameras such as the Microsoft Kinect are also widely used[20], but as mentioned before are not well suited for real world application.

The proposed system is an improvement on detecting the fall itself, as when a fall has already occurred, there is little a person can do to prevent it, especially if the person has some sort of physical disability or they are of older age. In addition falls have very specific profiles such as high accelerations followed by lack of significant movement. This makes fall identification simpler than fall prediction. The paper improves on existing state of the art, as it is able to detect multiple types of irregularities simultaneously, instead of simply distinguishing regular and irregular gait. In addition, it does so while maintaining high rates of accuracy

2. SYSTEM DESCRIPTION

Based on the wearer's learned gait parameters the system uses a variety of signals to identify events that may trigger a fall. According to gait analysis literature the events we chose to focus on were excessive trunk sway, small foot clearance and small foot width.

We measure these features using affordable commercial, small form factor sensors that can be worn in a way that does not impede regular gait.

2.1 Hardware Components

The wearable device utilizes the following sensors controlled by an Arduino Mega microcontroller.

- A Sharp IR infrared sensor to measure gait width.
- A VCNL4010 proximity sensor to measure foot clearance
- 3x Force sensitive resistors to measure which parts of the foot are on the ground. One is placed on the first metatarsal, one on the fifth metatarsal and one located under the heel
- 3x IMUs[25] located on the person's foot, shank, and lumbar area.
- 3x vibrating tactors providing vibro-tactile feedback placed at the foot, shank and lumbar area of the wearer.

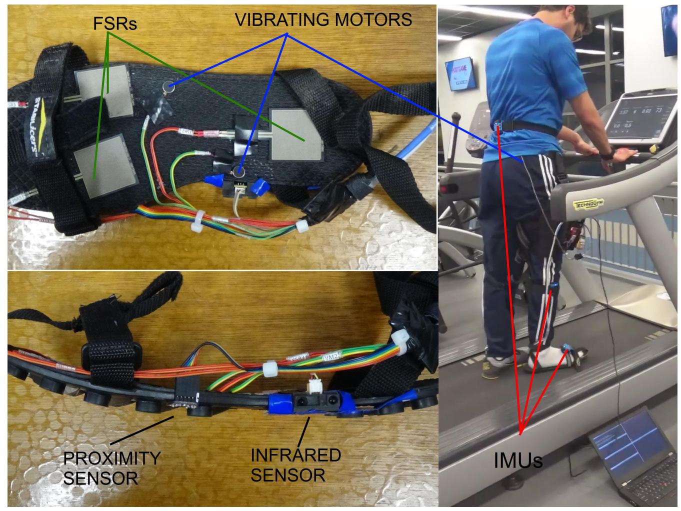

Figure 2: The wearable system.

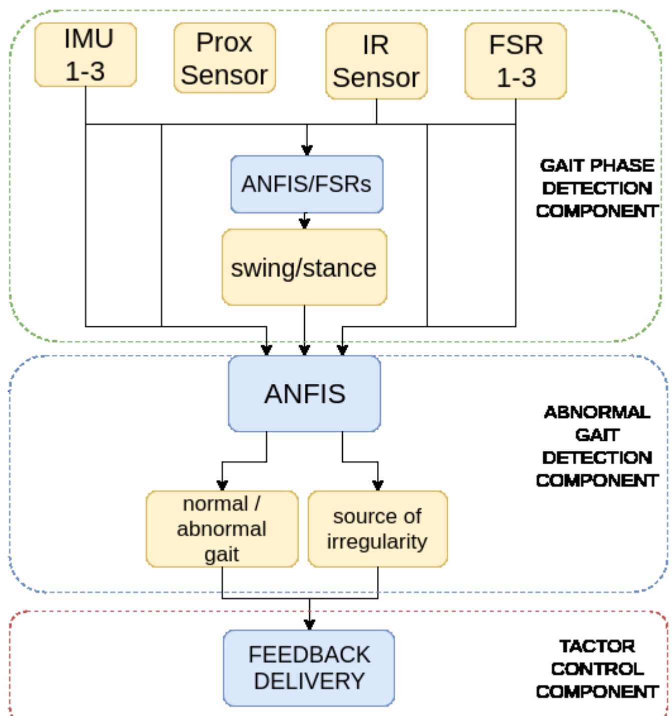

Figure 3: Overview of the complete fall prevention system.

The system consists of two distinct components (figure 3) and the hardware setup can be seen in figure 2. The device communication and recording framework was implemented in ROS(Robot Operating System) and is available as open source from the authors' lab code repository [15].

2.2 Data Acquisition

Data was collected from three healthy male subjects without any known gait disorders during a lab session (age: 27 ± 8.5 years, height: 184.6 ± 1.5 cm, weight: 76.3 ± 6.5 kg). The subjects were asked to walk on a treadmill at a pace that they felt comfortable with for five trials of two minutes each. During the first trial the subjects were asked to walk regularly. During each of the rest trials the subjects were asked to simulate one of the following: small foot clearance, small step width and excessive trunk sway, and a combination of all the previous gait patterns.

At a rate of $\approx 20Hz$ we collected the following signals: 3 FSR signals, 2 proximity signals from the IR and proximity sensors, and a 6 dimensional vector from each IMU consisting of accelerometer and gyroscope data, and the detected gait phase. This resulted in a 24 dimension input signal. The different gait events (Heel Strike, Flat Foot, Heel Off, Toe Off), and 3-D position of the subject were recorded as validation data using an 8 camera motion capture system at a frequency of 120 Hz.

2.3 Gait Phase Detection

With the existing sensor arrangement, the gait phase can be reliably identified by the FSR and IMU signals by using existing methods as described in the introduction. However an ANFIS has been implemented for gait phase detection with similar accuracy to the aforementioned systems (the specifics on ANFIS will be discussed in section 2.4.1).

2.4 Irregular Gait Detection

Falls can be caused by a number of factors, such as the nature of the terrain, inappropriate clothing and insufficient visual information about one's surroundings. For the elderly, deteriorating physical and mental condition attribute to falling in a number of ways. In our use case we consider three behaviors that have been identified as causes of falls: low foot clearance, small step width, and excessive trunk sway. By using each subject's specific data we are able to personalize the system to the individual's gait patterns.

2.4.1 ANFIS Structure

Fuzzy inference systems (FIS) are used to create input-to-output mappings using fuzzy logic[26]. These mappings are created based on a set of membership functions, fuzzy logical operations, and fuzzy rules that follow the general form of equation 1.

$$\begin{aligned} &\textbf{If } X_1 \textbf{ is } G_{1i} \textbf{ and ... } X_n \textbf{ is } G_{nj} \\ &\textbf{then } out_k = p_{k1}X_1 + ...p_{kn}X_n + r_k \end{aligned} \tag{1}$$

Here, $X_1, ...X_n$ denote the inputs of the system, and $G_{\alpha i}$ is one of the i possible fuzzy groups that input α might belong in. The parameters p_{ki}, r_k are used to determine the final outcome of rule k.

An Adaptive Neuro-Fuzzy Inference System (ANFIS) serves the same purpose as a single output Sugeno-type FIS, but it uses a hybrid learning algorithm to tune the membership functions. Figure 5 depicts the general form of a two input, single output ANFIS. In the presented system, input is represented as $X_1, .., X_n$, a vector containing the values of sensor signal averaged over a seven reading rolling window.

The defuzzified output represents the classification of gait as one of the four possible categories: regular gait, low foot clearance, small step width and excessive trunk sway.

Let $O_{l,i}$ denote the output of node i in layer l. Layer 1 nodes' outputs $O_{1,i}$ are the output of membership function i for the corresponding combinations of the two inputs.

In layer 2, $O_{2,i}$ are the products of the outputs of layer 1, where the product can be defined as before. We denote $O_{2,i}$ as w_i, to represent the firing strength of each rule.

In layer 3, the output $O_{3,i}$ or $\overline{w_i}$ denotes the normalized firing strength of each rule, and is calculated as:

$$\overline{w_i} = \frac{w_i}{\sum\limits_{j=1} w_j} \tag{2}$$

In layer 4 every node is an adaptive node with an output

$$\begin{gathered} O_{4,i} = \overline{w_i} f_i \\ \textbf{where} \\ f_i = (p_i x + q_i y + r_i) \\ \textbf{and } p_i x + q_i y + r_i \\ \text{are referred to as the } \textbf{consequent parameters} \end{gathered} \tag{3}$$

Finally, in layer 5, there is a single node with output

$$O_{5,1} = \sum_{i=1} \overline{w_i} f_i = \frac{\sum\limits_{i=1} w_i f_i}{\sum\limits_{i=1} w_i} \tag{4}$$

The learning component of an ANFIS consists of specifying the antecedent fuzzy sets and tuning the parameters of layer 4. This can be done through a hybrid learning algorithm presented in[12]. In a forward pass the algorithm uses the least squares method to adjust the parameters of layer 4. The errors are then propagated backwards and gradient descent is used to update the parameters that define the membership functions in layer 1, called premise parameters.

In the proposed work, we trained a number of systems for each subject in order to find the combination of sensor input that represented his/her individual gait pattern in the best possible way. The resulting systems were multi-input, single-output ANFISs (coded using Matlab's Fuzzy Logic Toolbox[1]). Although there were small differences between the models (for one subject the classifier presented slightly better accuracy when accelerometer data for one IMU was not used for training), every classifier utilized the gyroscope data provided by the IMUs, the FSR data, and the proximity sensor readings.

The final output of the system takes the values $0, 1, 2$ or 3 representing regular gait, small foot clearance, small step width and excessive trunk sway respectively. We used 60% of the data for training, 20% for validation and 20% for testing. We defined Gaussian membership functions for the input data as they have been shown to be compatible with the regular human gait cycle. We used the **product** and **max** as the **and** and **or** T-norms respectively.

To produce a crisp classification from the fuzzy output we calculate the mean of the last 7 outputs and follow the rule described in Algorithm 1. Here, t_i represents a threshold value chosen based on the training data for each user's different gait phases. To perform live classification, the system uses the 7 most recent inputs to classify the gait, using the same rule. This is done to avoid the effect of sensor data

Table 1: Classification Accuracy

	RG	LFC	SSW	ETS	IG	Overall
Subject 1	0.99 ±0.004	0.96 ±0.015	0.98 ±0.007	0.98 ±0.014	0.99 ±0.005	0.98 ±0.004
Subject 2	0.99 ±0.005	0.97 ±0.013	0.98 ±0.018	0.90 ±0.031	0.99 ±0.002	0.96 ±0.011
Subject 3	0.95 ±0.010	0.95 ±0.015	0.86 ±0.043	0.92 ±0.019	0.99 ±0.002	0.92 ±0.012

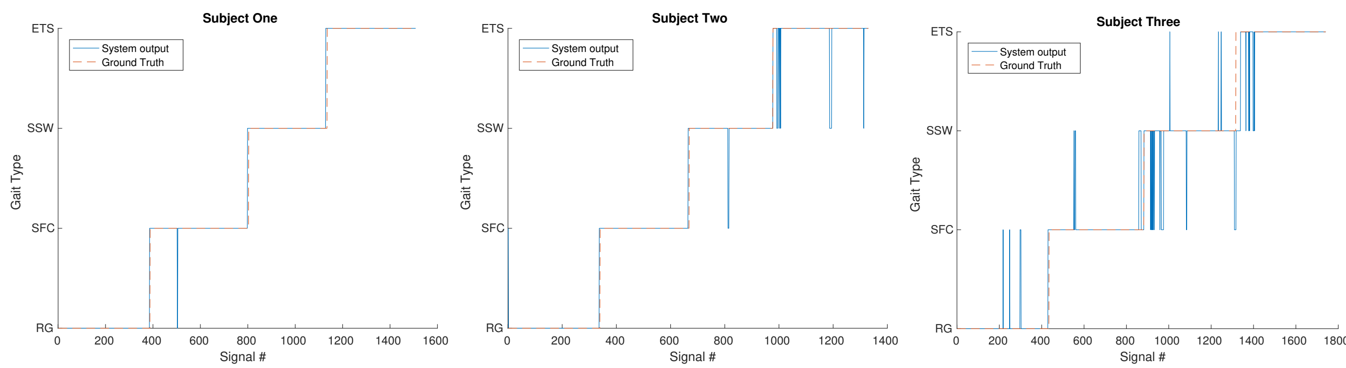

Figure 4: Example runs for the different subjects

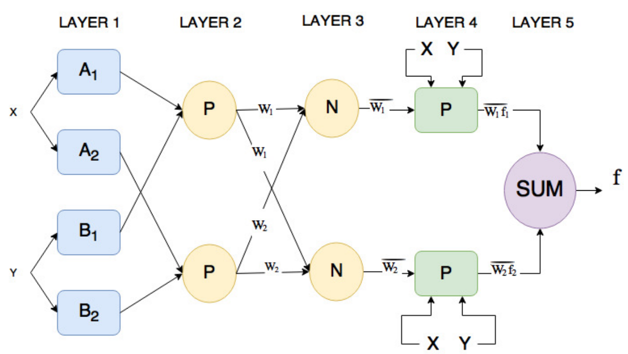

Figure 5: The standard form of a two input, single output ANFIS.

Algorithm 1 Defuzzification Process

procedure DEFFUZIFICATION
 out ← 7 most recent ANFIS outputs
 idx ← indexes of 7 most recent ANFIS outputs
 midx ← mean(idx)
 if midx< t_1 **then**
  class[idx] = 0
 else if midx< t_2 **then**
  class[idx] = 1
 else if midx< t_3 **then**
  class[idx] = 2
 else
  class[idx] = 3

spikes, and provide real time results.

3. RESULTS

The results for the different subjects can be seen in tables 1 and 2 for the different types of gait irregularities(where RG = regular gait, IG = irregular gait, SFC=small foot clearance, SSW = small step width, ETS=excessive trunk sway). As it can be seen in figure 4, the system identifies the exact irregularity occurring with a high degree of accuracy. In the case of subject 3 we observed a slight decline in accuracy for detecting low foot clearance and excessive trunk sway.

The proposed system was able to distinguish between regular and irregular gait with an accuracy of approximately 99% which is the same as the state-of-the-art in gait irregularity detection. In addition to identifying an irregularity in the gait pattern, it is important to also identify the parameters responsible for causing that irregularity. That would assist in delivering appropriate feedback and may improve gait performance.

We observed an average accuracy of 95% in classifying three different gait irregularities (low feet clearance, small step width, and excessive trunk sway) for the three subjects. These results are produced in real time (more than three system outputs per second) which is crucial for a supportive system. During the testing of the system we considered that only one type of gait irregularity would be occurring at any given time.

	Precision	Recall
LFC	0.956	0.977
SSW	0.916	0.947
ETS	0.956	0.939

Table 2: Precision and Recall of the system

It is also worthy to note that the subjects were healthy individuals trying to imitate irregular gait patterns. Therefore, they had good control over their movements and center of balance. In actual patients, we expect that this will not be the case, and those irregularities may have a more prominent profile.

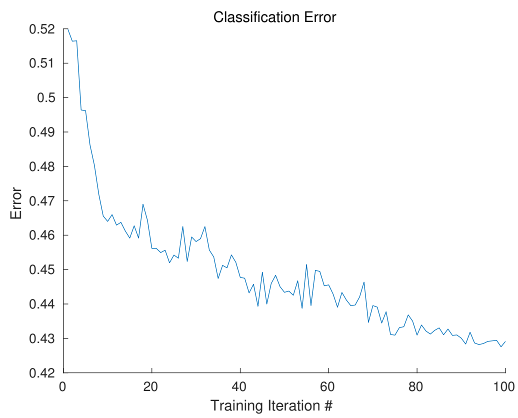

Figure 6: Error rate of the ANFIS system over 100 iterations.

4. CONCLUSIONS

In this paper we introduce a wearable system capable of reliably detecting three different types of irregularities in the wearer's gait that may lead to a fall. Identification of these irregularities may be used to produce feedback for gait correction and thereby reducing the probability of falls.

We implemented a system based on Adaptive Neuro-Fuzzy Inference Systems, that can successfully identify gait irregularities on a personalized basis. Existing work has focused on distinguishing between regular and irregular gait, while the proposed system can identify multiple types of irregularities, without loss in accuracy. Using this system, we hope that the user of the system will be able to receive informative real-time feedback to prevent falls, thereby reducing the monetary, health, psychological and social costs associated with fall injuries.

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