Detecting User's Behavior Shift with Sensorized Shoes and Stigmergic Perceptrons

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***Abstract*—As populations become increasingly aged, health monitoring has gained increasing importance. Recent advances in engineering of sensing, processing and artificial learning, make the development of non-invasive systems able to observe changes over time possible. In this context, the Ki-Foot project aims at developing a sensorized shoe and a machine learning architecture based on computational stigmergy to detect small variations in subjects gait and to learn and detect users behavior shift. This paper outlines the challenges in the field and summarizes the proposed approach. The machine learning architecture has been developed and publicly released after early experimentation, in order to foster its application on real environments.**

***Index Terms*—AAL, Long-term monitoring, Well-being assessment, Artificial Receptive Field, Stigmergic Perceptron.**

I. Introduction

Monitoring the Activities of Daily Living (ADLs) and detecting the deviations of behavioral patterns are crucial elements if we want to assess the quality of daily living [1]. Footwear is one of the most and common used medium, able to gather continuous information for long-term monitoring [2]. Several studies about monitoring gait quality have been presented in literature [3]. Moreover, loss of mobility is the common effect of many diseases and clinical conditions, such as neurodegenerative, Chronic Obstructive Pulmonary Disease (COPD), heart failure, frailty, and so on [4]. Change of gait patterns (e.g. gait speed, stance/swing duration, cadence, distance covered) can be associated to the future occurrence of severe clinical outcomes such as falls, hospitalization and even death [4]–[9]. Timely intervention in the identification of pathologies linked to the analysis of walking is of fundamental importance to counteract the symptoms that lead the patient to permanent disabilities. To date, mobility is assessed through patient self-reported outcomes or one-shot performance evaluation [10], [11]. Standard instruments able to assess gait and mobility (e.g. pressure sensing walkaways, optical motion capture systems) are accurate, but they only work in laboratory/clinical settings [12]. A large-scale-use, non-invasive system able to observe changes occurring over time, giving information about subjects wellbeing, can indicate initial signs of disease or deviations in performance. Internet of Things (IoT) devices are rapidly flooded the market in several and different contexts [13], [14]. However, user monitoring by IoT devices are often invasive and do not allow the user to naturally experience the period of control. This could also negatively affect the quality of the collected data, since the user would feel influenced by the monitoring device [15]. Thanks to recent advances in engineering of sensing, processing and artificial learning, such non-invasive systems can be based on miniaturized sensors, embedded in article of clothing, and multilayered learning architectures that can collect and model non-linear relationships in personal user's habits. In this context the Ki-Foot project[1] is inserted: the user wears a normal pair of shoes that are actually monitoring him silently and constantly, realizing a wearable solution for gait assessment in real life conditions. The wearable device market is increasingly gaining ground in today's society. In fact, we tend to be always connected with smart objects that communicate in the IoT world. Initially, it was possible to monitor some simple vital parameters, such as heartbeat or temperature, through smartwatch [16], [17]. The needs of users and research have forced this branch of technology to move towards devices that are less invasive and, at the same time, precise as possible. In this context, the sensorized shoes find ample space. The first models of shoes made for sport had high costs and consequently were not very successful. Similarly, failure also occurred with products made for specific medical applications, while the natural purpose is to exploit shoes to effectively monitor posture and user movements in a pervasive manner [18]. The sensors miniaturization makes the system less invasive and able to cover many scenarios than other solutions, bringing a great advantage to the user. Usually, sensors are integrated into insoles. As an effect, some significant issues need to be addressed, among which the difficulty in evaluating the initial position of the insole, as well as the sensors endurance to moisture and temperature, since it is in direct contact with the foot. In Ki-Foot project, instead, we develop a sensing shoe with integrated inertial

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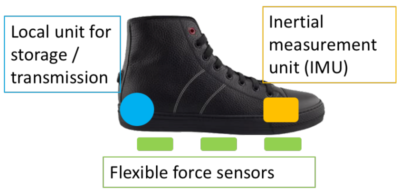
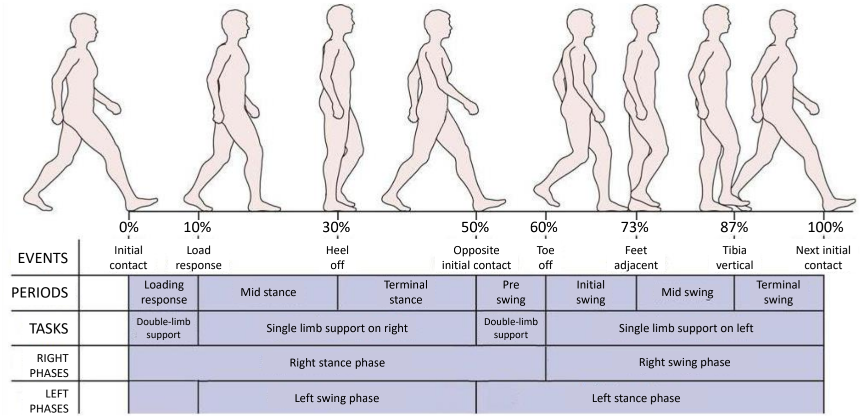


(a)



(b)

Fig. 1: (a) the sensing shoes prototype; (b) the stage of the gait cycle

and pressure sensors. The goal of the project is twofold: (i) to show the potential of the proposed system to learn from raw data and detect small variations in subjects gait on short-term mobility; (ii) to show the effectiveness of computational stigmergy to detect behavior shifts on long-term mobility.

II. Detection System

The principal core of the system is composed of smart shoes, that are sensorized footwear. Even if the smart shoes, from an aesthetic point of view, are not different from a normal pair of shoes, this new type of footwear is a technology and research concentrate. The upper side is made of leather and in this way it gives to the shoes a sporty and elegant design. The sole belong to "Gommus" line, that is a rubber sole line for high performances, high quality and high design products[2]. Inside the sole there is the integration of different sensors and Information and Communication Technology (ICT) components that allow an accurate analysis of different parameters, determine a correct gait and consequently can show abnormalities[3]. Sensors are completely integrated and hidden in the sole, they are made ad hoc in order to obtain the best precision in the measure and the best performances.

The Ki-Foot shoe, based on the Motus prototype developed by the project coordinator (Carlos s.r.l., Fucecchio, Italy), is shown in Figure 1a. The shoe has five pressure sensors integrated under the insole to monitor the mechanical interaction of the foot with the ground; three sensors under the forefoot, the remaining two under the heel. In this way an almost complete coverage of the entire surface of the sole of the foot is ensured. The pressure sensors are custom-made piezo-resistive transducers produced by using a conductive material on a flexible substrate. Force sensors are sampled at 50 Hz. This kind of sensors has already been tested in different scenarios like sleep monitoring with smart bed slats [15]. A digital inertial measurement unit is integrated in the frontal part of the shoe. It consists of a 9-axis IMU inertial platform with a 3D accelerometer, a 3D gyroscope and a 3D magnetometer. Each value of the accelerometer represents the measure of the acceleration of the corresponding axis and it is measured in mg (milli-gravity). The gyroscope measures the angular speed for each corresponding axis and is expressed in dps (degrees per second). While, the magnetometer indicates the measurement of the earth's magnetic field for each axis and is expressed in mG (milli-Gauss).

A Bluetooth 4.0 transmission module is integrated with the rest of the electronic unit in the heel of the shoe to enable low-energy data transmission to a mobile device (smartphone, tablet). In fact, the rechargeable battery type LIPO allows a complete operation of the system for 48 hours. In this way, the shoes ensure a complete measurement of the characteristics of the static and moving foot. Furthermore, being completely wireless controlled via a smart device, the subject is not conditioned during movement and can move freely and independently for several days. Thanks to these sensors and to these measures, there is a realistic analysis of the step and the characteristics of the two feet independently.

[2]http://www.gommus.it
[3]http://www.adatec.it

III. Gait Analysis

In order to better understand the complexity of the movements and events that occur between one step and the next, it is necessary to divide the gait into a cycle (walking cycle). A gait cycle is defined as the time between two successive supports of the same leg on the ground. As shown in Figure 1b, a gait cycle is then divided into two distinct phases:

- Support phase (Stance), i.e. the time interval in which the leg remains in contact with the ground. It starts when the heel of the foot touches the ground (Initial contact) and ends when the tip of the same foot comes off the ground (Toe off).
- Transfer phase (Swing), i.e. the time interval in which the leg remains raised above the ground. It starts when the toe leaves the ground (Toe off) and ends when the heel of the same foot touches the ground (Next initial contact).

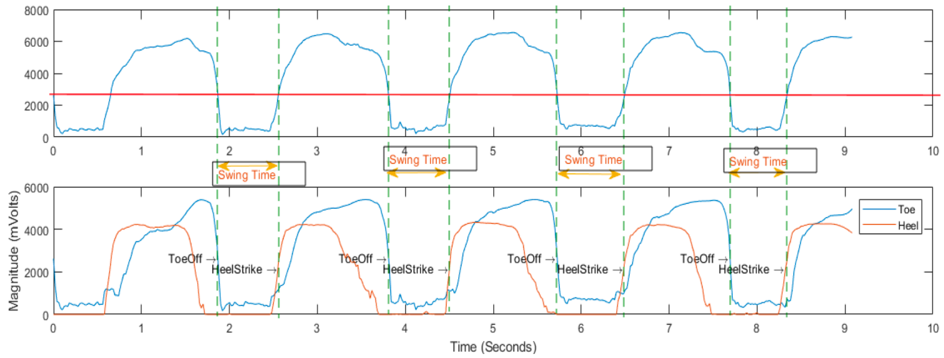


Fig. 2: Swing time evaluated from the flexible force sensors

The stance phase occupies 60% of the gait cycle and is divided into 4 periods [2]:

- Loading response (10%) also known as foot flat, is the time interval during which the foot absorbs the weight of the body due to contact with the ground.
- Mid stance (20%) during which the body is supported by a single leg. In this phase the body begins to move, transforming the force of absorption of the impact into a propulsive force.
- Terminal stance (20%) begins when the heel comes off the ground and the body weight is spread over the metatarsal heads.
- Pre swing (10%) during which the hip becomes less extended, the knee flexes and the plantar flexion increases. At the end of this phase the foot comes off the ground.

The swing phase occupies 40% of the gait cycle and is divided into 3 periods:

- Initial swing (13%): during this phase the hip extendsand then flexes.
- Mid swing (14%), during which the hip flexes, the ankle becomes dorsiflexed.
- Terminal swing (13%) begins with a hip flexion, a blocked knee extension, a neutral ankle position and ends with foot heel contact with the ground.

In the gait cycle it is also possible to distinguish two independent tasks:

- Single limb support i.e. the time interval during which only one limb touches the ground.
- Double limb support i.e. the time interval during which both limbs touch the ground.

IV. Signal Processing and Behavior Shift Assessment

In this Section, we present the approach used for assessing behavior shifts from the data gathered by the sensorized shoes. Behavior shift is a pattern used in many applications: it may indicate initial signs of disease or deviations in performance [1], [17], [19]. Here the modification of gait characteristics is considered a possible signature of disease.

As a first step, relevant features are extracted via a feature reduction policy, to be able to classify the traces provided by the shoes. In some sense, the extracted features act as ”fingerprint” of a trace. As a pilot scenario, let us consider three common features, selected to measure the mobility behavior drift; i.e. the cadence, the Coefficient of Variation (CoV) of the stride time and the CoV of the swing time. The cadence is the number of steps in a minute, while the stride time is defined as the time elapsed between the first contact of two consecutive footsteps of the same foot (i.e. swing and stance phases) expressed in milliseconds. As a proof of concept Figure 2 shows the pressure magnitude of the toe (blue line) and of the heel (orange line) during a walking session. As shown in Figure 2, to evaluate the swing time we can evaluate the mid cross of the total pressure on the shoe. Figure 3 shows the measured stride time during a walk. The signal is the total pressure of all flexible force sensors by a given leg. As highlighted in Figure 3, the stride time is calculated evaluating the time instants where each transition of the input signal, crosses the 50% reference level.

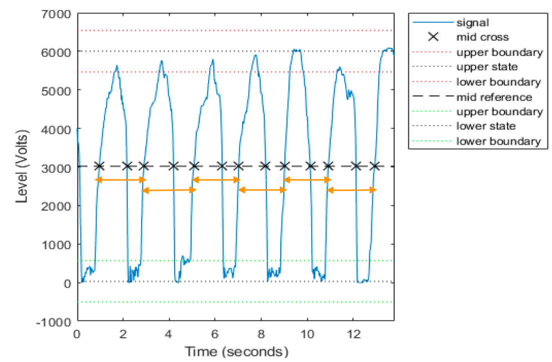


Fig. 3: Stride time evaluated from the flexible force sensors

The samples provided by the three features are used to learn the user's habit and to assess a possible behavioral shift. Specifically, the input samples are aggregated into functional structures called trails. Trails are created by using computational stigmergy, a bio-inspired mechanism of spatio-temporal micro clustering [17], [20]. The trailing process is managed by computational units called Stigmergic Receptive Fields (SRFs) [21], which provide a (dis-)similarity measure between sample streams. The dissimilarity measure can be quantified by the training process to serve as: (i) a micro-pattern detector, used for information granulation; (ii) a behavioral anomaly indicator, with an intuitive interpretation based on the experimental user's evidence. Specifically, SRFs are organized into layers, called Stigmergic Perceptrons [17], and parametrically adapted to contextual behavior by means of a Differential Evolution algorithm [22].

The novelty of the undertaken study relates to the multilayer architecture of the stigmergic preceptrons and the way in which the receptive fields are formed and adapted to the problem of behavioral shift. Each SRF acts as a general purpose local model (archetype) that detects a micro-behavior of the entire modeling domain. Since micro-behaviors are not individual, a receptive field can be reused for a broad class of patients/users. The Stigmergic Perceptron is a more general and effective way of designing micro-pattern detection; moreover, the Stigmergic Perceptron can be used in a deep learning architecture, thus providing further levels of processing so as to realize a behavioral macro analysis on long term.

V. Conclusion

This paper summarizes the research activity carried out in the Ki-Foot project for monitoring behavior shift. The raw sensor data are pre-processed in real time to extract temporal gait parameters (stride time, stance/swing duration, cadence). Such parameters, periodically sampled, feeds machine learning algorithms in order to detect the modification of the gait characteristics as a possible signature of disease. The project is strongly focused to the pathologies and conditions affecting elderly people. The proposed approach is based on stigmergic computing paradigm and sensorized shoes. The challenges in the field are outlined, the approach is illustrated. The proposed architecture has been developed and is being experimented, making possible the initial roll-out of the approach into real environments. The source code of the Stigmergic Perceptron has been publicly released on the Github platform. The interested reader is referred to [23] for further architectural details. Other pilot case studies are currently undertaken, to demonstrate that the system is effective in achieving the expected performance on a number of cases.

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