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User Tracking for AAL: an inertial approach

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Abstract **– This paper deals with a novel multi-sensor approach for the implementation of a tracking system exploiting features of smartphones. Actually, the widespread use of smartphones and performances provided by the variety of sensors embedded in these devices encourage their use in mobility oriented applications, such as the exploitation of educational/job environments by weak people.**

The proposed methodology exploits information provided by the multisensory features embedded in a standard smartphone and advanced paradigms to improve the efficiency of the system in performing user tracking tasks.

I. INTRODUCTION

The monitoring of daily activities performed by weak people is a topic that strongly stimulates the scientific community as it faces problems of technological and social interest. The monitoring of daily activities requires the knowledge of the user's location within the environment, in order to assess the user-environment interaction and to provide an efficient assistance for each specific situations.

Some indoor positioning systems require a structured environment [1]. These systems suffer for problems related to a discontinuous form of information, low accuracy and high installation costs. Some systems use trilateration techniques based on ultrasound sensors aimed to improve the localization accuracy as compared to RF based solutions. These architectures require the installation of dense networks of environmental nodes [2].

Inertial navigation systems could be effective solutions to be adopted in unstructured environments, although they suffer for accumulative drift error and often require training phases with the end users [3]. The latter could be very discouraging for the users.

Another point to be kept in mind is related to the user interface which should be user-centered and easy to use. A convenient solution to fix drawbacks above mentioned could be represented by smartphone based devices.

It must be observed that the opportunity of using smartphones for weak people in AAL context is a controversial topic as it is led to believe that these devices are not user-friendly. Actually, the sensing features embedded in smartphones, the possibility to implement complex and well performing paradigms as well as suitable user interfaces, make such approach very interesting [4-5], also in the framework of skilled users. Moreover, it must be observed that features of well designed smartphone based assistive systems can be exploited also by non expert users.

This paper deals with a novel approach to perform the estimation of the user walking distance. Main novelties introduced by the proposed solution concern both the methodology for the step identification and the procedure to properly fit the walking model to the user.

Although the strategy proposed is quite general and not strictly related to the adopted hardware architecture, the system proposed exploits a smartphone and its embedded sensors and processing features. Anyway, it must be considered that interfacing capabilities of smart phones, such us wide touch screen and Bluetooth headset, are strategic to implement an effective interaction between the user and the AAL system.

The step recognition tool exploits a dedicated paradigm processing information given by the inertial sensor. Concerning the walking distance estimation, two different models are taken into account for the sake of benchmarking while two methods to fit models on the user dynamics are addressed.

A wide set of tests has been performed in supervised mode involving several users walking freely along 10 different paths (without any walking mode constraint).

Main advantages of the proposed approach, as respect to State Of The Art, reside in the reliability of the step identification and walking distance estimation procedures, as well as the real applicability of the procedure proposed to fit walking models to the user dynamics. Such features make the tracking system really user oriented.

It must be remarked that the possibility to combine information on the user position and the environment allows to manage the user/environment interaction, thus improving the quality and the efficiency of a safe environment exploitation by weak users. Addressable application contexts of the developed solution could be related to the exploitation of museums, schools and public buildings.

II. THE PROPOSED STRATEGY FOR WALKING DISTANCE ESTIMATION

The reconstruction of the distance traveled by the user is mainly based on human gait reconstruction with particular regards to steps recognition and the estimation of walking distance between two consecutive steps. To

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such aim dedicated paradigms have been developed, which take into account dynamics correlated to real operating conditions such as the smartphone position on the user body and asymmetry in the human gate.
A schematization of the step detection algorithms is shown in Fig.1. Actually, the vertical component of the acceleration signal provided by the tri-axial accelerometer embedded in the smart phone is used. A step is identified when the accelerometer signal falls below a TL threshold after it overpasses the TH threshold. Moreover, constraints shown in Fig.2, on the maximum distance between the two crossing events and on multiple subsequent crossing of the TH threshold, have been included to reduce false positives.

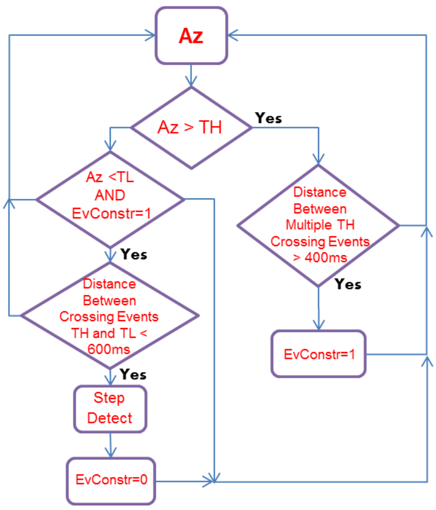


Figure 1 –Flow Diagram of the Step Detection Algorithm.

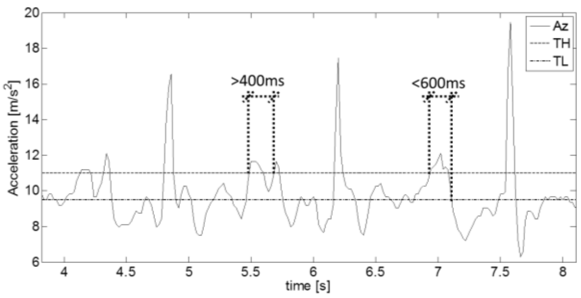


Figure 2 – A graphical representation of the constraints adopted by the step detection algorithm

In order to estimate the distance travelled between two consecutive steps two approaches have been used. The first one exploits a fixed step size, while the second algorithm uses the inertial dynamics between each pair of steps.
The Static Model, SM, uses a fixed dimension for the step size, ΔS_{stat}, which is empirically estimated during a preliminary tuning phase, where the user is requested to walk along a well-defined path. The Walking Distance (WD_{stat}) estimation is based on the following model:

$$WD_{stat} = N \cdot \Delta S_{stat} \quad (1)$$

where N counts for the step number.
Drawbacks of this approach resides in the poor accuracy in the estimation of the walking distance in case of mixed paths, where the user can modify his walking behavior (e.g. walking speed and step size).
The second approach, Dynamic Model (DM), exploits the step frequency, f_k, and the variance of the accelerometer signals between two steps, υ_k, to perform an adaptive and real time estimation of the Step Size (ΔS_{Ad})" [6]. The Adaptive Walking Distance (WD_{Ad}), is computed by the following model:

$$\mathrm{WD}_{Ad} = \sum_{k=1}^{N} \Delta \mathrm{S}_{Ad}^{k} \quad (2)$$

with

$$\Delta S_{Ad}^{k} = \alpha \cdot f_k + \beta \cdot \upsilon_k + \gamma \quad (3)$$

$$\upsilon_k = \frac{\sum_{j=1}^{M} \left(a_j - \bar{a}\right)^2}{M}; \quad a_j = A_z; \quad f_k = \frac{1}{T_k - T_{k-1}} \quad (4)$$

where M is the number of samples between two consecutive steps; A_z is the vertical component of the acceleration, T_k is the time of the k step [7].
As a preliminary study to assess the suitability of the proposed strategy, experiments have been performed in a supervised mode by users in good health, which were asked to perform paths at different walking speed (Slow, Medium and Fast), as well as paths without any kind of constraints on the walking dynamics (called Mixed paths).
Patterns have been divided into two groups: learning paths and test paths. Dimensions of the two groups will depend on the adopted fitting approach and will be defined in the next Section.

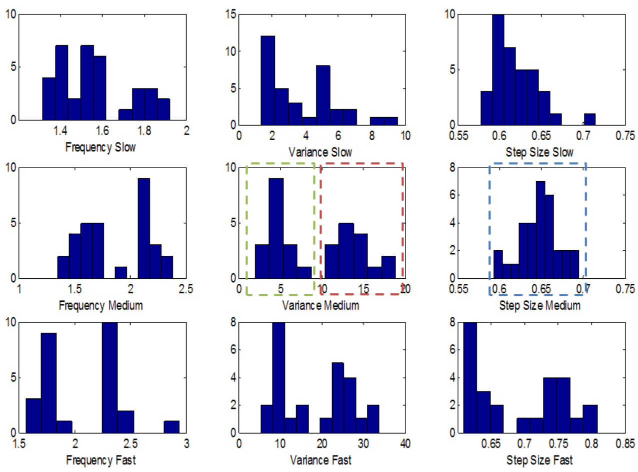


Figure 3 – Distribution of measured frequency, variance and step size for a single user running 20 m long walking path at different speed: slow, medium and fast

Figure 3 shows results related to the measured variance, frequency and step size for a single user running along a 20 m walking path at different speeds: slow, medium and fast. As it can be observed, above quantities are not uniformly distributed, with particular regards to the variance which is well defined by two separate data set. This behavior is mainly related to asymmetries in the human walking dynamic. The separation threshold has been defined for each user by the learning patterns.

Observed behaviors led to the need of defining two different models for the estimation of the adaptive step size, for the two classes of identified variance, as schematized in Fig.4.

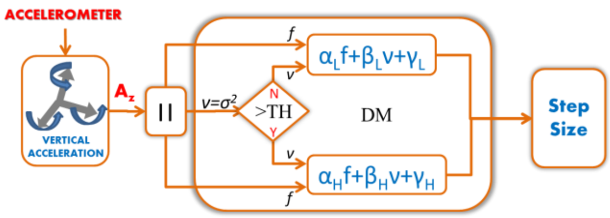


Figure 4 – Schematization of the methodology for the step size estimation

III. THE FITTING APPROACH AND EXPERIMENTAL RESULTS

In this section results obtained by a lab-scale prototype of the system above described are discussed. The prototype is based on the use of a commercial smartphone with embedded inertial sensors. A dedicated Android App has been developed which manages sensors' data acquisition and the WiFi communication with a PC. The latter run a GUI interface developed in the LabVIEW™ environment, which allows for monitoring and managing sensor signals.

Experiments have been performed in two phases: the learning phase aimed to the estimation of ΔS_{stat}, $\alpha_L,\beta_L,\gamma_L$ and $\alpha_H,\beta_H,\gamma_H$ parameters, and the test phase to assess the system performances.

Users are requested to perform several paths. As first, each user walks along paths of 20 m with a Slow, Medium and Fast speed. Moreover, each user is requested to perform 10 mixed paths of 35 m, without any constraints on the walking dynamics (e.g. speed, step size).

The first set of paths (20 m long) are used to set the static step size, ΔS_{stat}, at the Medium speed.

Two different approaches have been used to fit the model (2) to each user. In the first method six mixed paths were used as the learning set and four mixed paths as the test set. The second approach uses one path to estimate the model parameters (learning phase) and the other nine paths to test the model. In the latter method all pattern combinations have been assessed.

Model parameters have been estimated by the Nelder-Mead algorithm minimizing the following performance index:

$$J_{wd} = \left| WD^{Nom} - WD^{Estim} \right| \qquad [m] \qquad (5)$$

where WD_{Nom} is the expected walking distance, while WD_{Estim} is the walking distance estimated by models (1) or (2).

Results obtained by applying the two fitting methods above mentioned are summarized in Table 2, which reports, for each user, the average performance estimated during the test phase by the SM and the DM. Results for both the mixed paths and the Slow, Medium, Fast paths have been reported.

As expected and evincible by Table 2b, the SM performs well and sometimes better than the DM in cases of uniform speed paths (Slow, Medium, Fast), while the DM performs well also in case of mixed paths (see Table 2a).

Concerning the two fitting approaches, it can be affirmed that the first methodology which uses a large learning set performs better than the second approach. Anyway, it must be observed that from a practical point of view, in real application contexts it is definitively more convenient to be able to estimate the model parameter for that specific user by a short learning phase rather than by a long one. Concluding, it can be affirmed that obtained results encourage the use of the second method for the sake of model fitting.

As an example, Figure 5 shows the comparison between performances of the SM and the DM for the four test paths in case of the User 3.

	Method 1		Method 2
	SM	**DM**	**DM**
User 1	6,03	0,52	0,81
User 2	5,00	0,27	0,51
User 3	3,83	0,52	0,71
User 4	6,13	0,54	0,61
User 5	2,15	0,29	0,71
User 6	4,42	0,39	0,56
User 7	5,16	0,62	0,95
User 8	7,00	0,29	0,33
User 9	3,18	0,47	0,55
User 10	2,63	0,45	1,01
Average	**4,55**	**0,44**	**0,67**

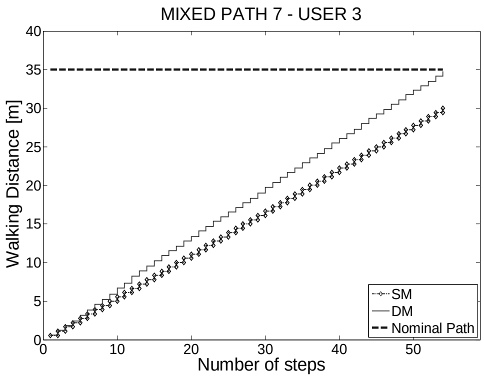
a) TEST over Mixed Paths

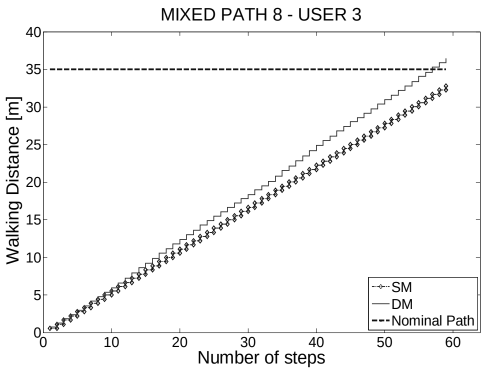
	Method 1		Method 2
	SM	**DM**	**DM**
User 1	1,89	2,55	1,27
User 2	2,90	1,65	2,51

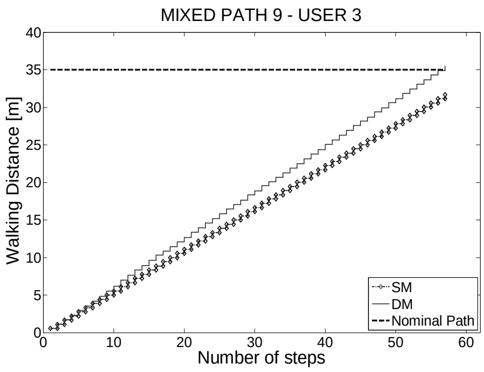
User 3	3,33	3,79	2,89
User 4	1,79	1,95	1,94
User 5	2,73	1,92	2,13
User 6	2,11	2,74	2,48
User 7	2,11	2,40	3,12
User 8	3,42	3,21	3,44
User 9	1,47	1,21	1,84
User 10	2,19	2,35	2,18
Average	**2,39**	**2,38**	**2,38**

b) TEST over Slow Medium and Fast Paths

Table 2 - Average of the Mean Performance Index obtained with the two learning methods for all of users for walking path a)Mixed Speed b)Slow Medium Fast Speeds







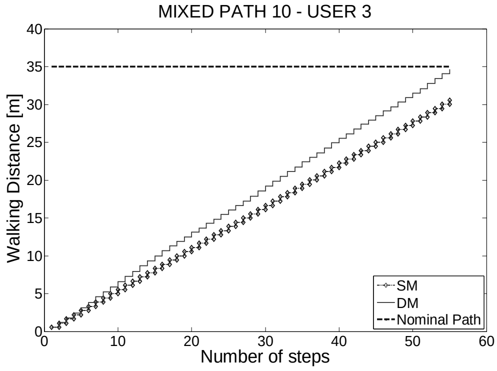


Figure 5 – WD_{stat} and WD_{Ad} performances in case of test patterns of one user. Four different paths walked with mixed walking speed during the execution of the test. Two different step sizes have been used.

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