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MuSA: a multisensor wearable device for AAL

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Abstract—**In this paper, a novel multi-sensor wearable device, called MuSA, is introduced. MuSA aims at integrating in the CARDEA ambient-assisted-living framework: on the one hand, MuSA provides CARDEA with useful ambient-intelligence features, such as localization and identification; on the other hand, it may borrow from the environmental control system many infrastructural and communication components, resulting in a less expensive implementation. MuSA exploits on-board sensors and signal processing units for fall detection, heartbeat and breathing rates detection. At this level too, sharing of part of the circuitry enables power and cost savings. Ubiquitous computing paradigm is followed, carrying out all of the signal processing and decision processes at the wearable node: this makes communication toward supervision levels much less demanding and independent on the actual physical features of the sensors themselves. Test have been carried out, confirming that the low-cost approach which has been followed still allows for adequate quality of responses. Field test is starting, to evaluate psychological and ergonomic aspect as well.**

INTRODUCTION

POPULATION ageing is putting to severe proof current health- and social-care models: the relative number of people experiencing frailty and disability conditions due to old age is increasing, so that conventional caregiving schemes are becoming hardly sustainable. In particular, institutionalization is frequently exploited to provide care to lone elderly. This practice, however, implies high costs (besides potentially threatening quality of life), and cannot be easily scaled to the increasing number of older people needing assistance: hence, home care and home assisted living strategies are an essential component of present and future care policies. Tools based on information and communication technologies may play an enabling role, allowing for the implementation of many assistive functions in the home environment, aimed at autonomy and independent life. To this purpose, basic needs to be accounted for are related to ambient safety and security, as well as personal and health monitoring. In this paper, an integrated approach to such issues is described. The CARDEA system [1] encompasses within the same framework many functions which are customarily carried out by independent entities: CARDEA relies on standard IP communication techniques (even at the field level) and is inherently based on distributed intelligence techniques. On-board processing is extensively exploited by ambient sensors and wearable sensors, aiming at reducing communication overheads, increasing reliability and reducing costs. An open and flexible architecture is implemented, allowing for reconfigurability and interoperability. Remote access and control of every device is enabled through web-based tools.

In the following section, the CARDEA framework is introduced, emphasizing the adoption of distributed-intelligence ambient control modules. Then, MuSA wearable wireless sensor platform is described. Conclusions and ongoing work are eventually discussed in last section.

CARDEA

CARDEA[1] is a powerful and versatile Ambient Assisted Living (AAL) system, developed at University of Parma.

Fig. 1 CARDEA system view

The system is inherently based on standard IP communication, and has a hierarchical structure, easily scalable from the single apartment to large residential complexes. An intelligent module, called FEIM (Field Ethernet Interface Module) has been designed and implemented to cope with a wide variety of sensor devices: FEIM module allows for connecting low-cost sensors, even if not conceived for network connectivity.

FEIM is based on an embedded microcomputer, and can be programmed to control analog and digital multiple field devices (up to 25 per module). Local processing power is also exploited to implement low-level decision strategies (light or appliance control, for instance) or safety-critical tasks (alarm messaging) making them independent on actual availability of network connection. FEIMs communicate among them on a peer-to-peer basis, requiring no external supervision, allowing for establishing operating rules involving different device clusters.

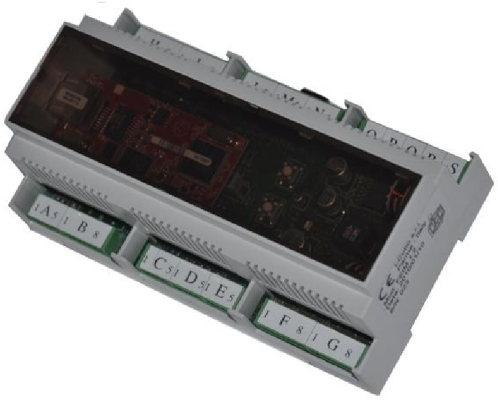

Fig. 2 FEIM module

Also, dynamic reconfiguration is exploited to implement fault-tolerant policies and graceful degradation strategies, by accounting for redundant configurations and module hot-swapping. At a higher hierarchical level, supervisor processes, running on any networked machine, are exploited for the implementation of more complex operating rules and to deal with user's interfaces and external network gateways. CARDEA includes a number of user interfaces, easily accessible and suitable for elderly people and people with disabilities [2]. It also features a web-extension module, which enables full control and monitoring functions from any remote location, by means of dynamic web applications [3].

A wireless sensor network (WSN) contribute to the system architecture as well, dealing with mobile devices. Here, we shall refer to a WSN based on the IEEE-082.15.4 (ZigBee) standard protocol, exploited for the implementation of wearable sensors described in the following.

CARDEA-MUSA

Wearable devices are exploited to monitor personal activities and vital signs. They are conceived to provide continuous monitoring, so they need to be small and lightweight, and minimally intrusive. Also, battery power should last as long as possible, this calling for accurate management of the power budget. Finally, being such devices exploited for security and health purposes, high reliability, as well as ease of use and reconfigurability [4], are mandatory. Of course, inexpensiveness is needed to allow for large-scale deployment.

CARDEA MuSA (MUlti Sensor Assistant) is a wearable multisensor platform, specifically designed with assistive purposes, compliant with ZigBee/IEEE802.15.4 standard protocol. MuSA is designed to be worn at belt or at chest: it is quite small (78x48x20 mm), and lightweight (about 70 grams, Li-Ion battery included). Different functions can be implemented on the same platform: basic configuration of MuSA includes a call button, automatic fall detection and an indoor localization function. The latter function can be exploited in large residential complexes, allowing CARDEA to make caregivers aware of the actual position of a person needing assistance, or to detect wandering behaviors of cognitive-impaired people [5]. CARDEA MuSA can be extended with further functions, hosted by the same hardware platform: a basic ECG system is implemented, used to evaluate heart rate. A breath rate detector is included as well, based on chest expansion measurement. All of the signal acquisition and processing is carried out by MuSA on-board circuitry: detection of abnormal behaviors or deviation of vital signs from their "normal" range is carried out by MuSA. Radio communication is hence kept at a bare minimum (alarm messages and network management), saving battery energy.

MuSA board is based on CC2531 system-on-chip [6] by Texas Instruments. Two basic building blocks can be identified: a IEEE 802.15.4 radio transceiver, and a microcontroller taking care of ZigBee stack management. The same microcontroller is exploited for digital signal processing. The board also include sensors and analog front-end circuitry needed to acquire vital signs.

Fig. 3 MuSA wearable device

MuSA is fully integrated in the CARDEA framework: a network of ZigBee fixed-position nodes is deployed into the environment, and managed by CARDEA. Such nodes exchange information with MuSA mobile devices, and make them available to CARDEA, either by exploiting a FEIM interface channel (i.e., similarly to environmental sensors) or directly at the supervision level, communicating with supervising processes through a TCP/IP socket. Then, all of the communication features of CARDEA (web-based remote management, phone or SMS messaging, etc.) are straightforwardly available to MuSA, with no need of replicating such features in a stand-alone MuSA base-station.

A. Fall-Detection

The fear of falling is a major issue, threatening elderly self-confidence and independence. Falls are one of the first causes of death or serious injury in older adults [7]: the use of automatic fall detection systems could both speed up the assistance of the people in need and give a security feeling to the person using it. Perspectively, behavioral analysis of people's motion (gait quality, for instance, based on the same accelerometric patterns exploited for fall detection) can be exploited for possibly preventing fall conditions.

There are several ways to fall: the fall movement can be quite different, depending heavily on the actual situation. In [8] a fall classification attempt is presented; the author identifies three different kinds of most common falls for an older adult: fall during sleep, from the seated position and from standing up to lying on the floor. Whereas the first two can be somehow monitored by means of bed- or chair-occupancy sensors managed by CARDEA, the last one (also being the most frequent kind) calls for smarter automatic detectors [9]. Fall detectors may exploit artificial vision algorithm, environmental sensors and wearable sensors. Wearable sensors provides a fair trade-off among cost, performance and intrusiveness: the adoption of a wearable device, moreover, also provides CARDEA with identity information, enabling management of personalized settings and behaviors.

At the heart of fall detector, the low-power LIS331DLH [10] triaxial MEMS accelerometer manufactured by ST Microelectronics is used for algorithm implementation.

Basic fall detection algorithms exploit threshold comparison [11]: since falls are often associated to acceleration peaks, current acceleration (the Euclidean norm of the acceleration vector, actually) is checked against a given threshold, which depends on personal physical features (height, weight, …). However, tuning such a threshold is critical, with respect to false-positive and false-negative conditions: many daily-living activities may result indeed in accelerations comparable with those involved in a fall (stumbling, sitting down or standing up, bending down, …). Hence, a more reliable detection strategy is needed: to this purpose, MuSA correlates acceleration pattern with postural information. Body orientation can be easily inferred by exploiting further sensors such as gyros or protractors, introducing however additional costs, size and power constraints. We therefore exploited digital signal processing to extract relative orientation information from the same stream of accelerometric data. The MEMS accelerometer, in fact, is subject to the gravity acceleration G, which can be regarded as a "static" component of the sensed acceleration. Static acceleration can be extracted from the sensor output stream by proper filtering, thus providing a reference that can be used to calculate the angle shift between subsequent estimations [20].

A differential approach is followed, which makes the algorithm independent on the actual sensor-wearing fashion. Whenever an acceleration peak exceeding the threshold is observed, a comparison between the orientation before and after the peak occurrence is carried out.

The algorithm is illustrated in Fig. 4: acceleration components (A_x, A_y, A_z) are acquired from the MEMS every 16 ms. Then, the acceleration norm is computed, and acceleration components are stored for subsequent processing. When the norm exceeds the given threshold, comparison of static accelerations starts, looking for the tilt angle computed just before and after the acceleration peak.

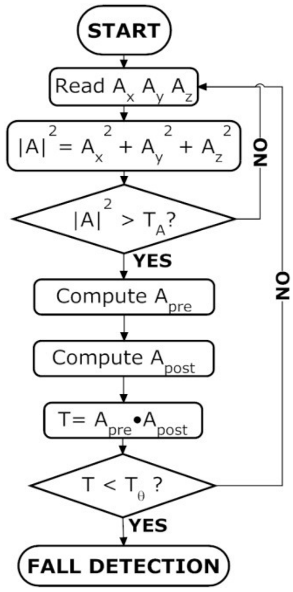

Fig. 4 Fall detection algorithm flowchart

A_{pre} is static acceleration (i.e., steady state) component, averaged on a 1 sec time interval prior to the acceleration trigger, while A_{post} refers to the same average component, computed after the trigger. Averaging allows for noise reduction, and the dot product between pre- and post-peak average accelerations can be computed:

$$T = A_{pre} \cdot A_{post} = \sum_i A_{pre\_i} A_{post\_i} \quad (1)$$

Since the intensity of A in both cases should be equal to G, the tilt angle θ can be readily worked out:

$$T = |A_{pre}||A_{post}| \cos\theta = G^2 \cos\theta \quad (2)$$

and compared with a suitable threshold, in order to infer an actual fall.

So doing, data coming from a single accelerometer provide both acceleration and (relative) tilt-angle estimate.

The algorithm reliability has been verified through some tests, following the methodology introduced in [12]. We tested MuSA on a set of twelve volunteers (20-30 years old, 51-78 kg weight, 163-192 cm height), who were asked to simulate different kind of falls from the standing position (backwards to sitting position, backwards to lying position, forward to knees, laterally to right side, laterally to the left side). Then, the volunteers were asked to perform daily living activities, suitable for being mistaken for falls (recovering standing position from previously described falls, sit down on a chair, stand up from a chair, sit down on a stool, stand up from a stool). Every test was repeated five times by each volunteer, summing up to 840 records in the database.

By considering the number of True Positives (TPs) and the number of False Negatives (FNs) we may evaluate the sensor sensitivity, i.e., the ability of recognizing actual falls:

$$Sensitivity = \frac{TPs}{TPs+FNs} \tag{3}$$

For the given test set, a 99 % sensitivity figure was achieved. Similarly, taking True Negatives (TNs) and False Positives (FPs), we may evaluate sensor effectiveness in discriminating misleading events:

$$Specificity = \frac{TNs}{TNs+FPs} \tag{4}$$

A 97.8 % specificity figure was estimated on the given set.

The algorithm, although relying on limited computational power available, is hence quite accurate; data processing and interpretation is carried out by MuSA on-board processor, which hence can be seen by CARDEA as a simple binary sensor, signaling falls by means of a Boolean variable.

A low-power operating mode has also been implemented, exploiting LIS331DLH features to reduce MEMS sampling frequencies. In fact, acceleration threshold and orientation can be monitored by the MEMS device itself, relieving the microprocessor from continuously checking the data stream. The CPU is awaken by the accelerometer (through an interrupt line) whenever an over-threshold acceleration is detected. In normal conditions, CPU activity is hence limited to coarse sampling of accelerometer registers (acceleration and orientation). This allows for better exploitation of sleep modes, at the expense of a less detailed recording of motion data: by tuning time intervals, we were able to attain a 50% reduction in the processor power consumption, with a negligible degradation in sensitivity and specificity.

B. Heartbeat Detection

CARDEA MuSA is also capable of estimating the heartbeat rate. This can be exploited to promptly notify abnormal heart rhythms (i.e., arrhythmias, tachycardia or bradycardia), or, when combined with motion data, to provide a more accurate picture of the energy expenditure. A simple electrocardiogram (ECG) section is exploited to this purpose. Diagnostic systems usually rely on a variable number of body electrodes, placed at specific configuration patterns (leads) [13]: of course, ECG definition and accuracy increases with the number of electrodes and leads acquired, providing more physiological insight. MuSA, however, aims at continuous monitoring and is not conceived as a diagnostic tool: then, in order to limit sensor intrusiveness and to cope with circuit size and power consumption, we adopted a simple, two-electrode scheme [14], which enables, depending on the actual body placement of electrodes, exploitation of three fundamental Einthoven leads. On-board circuitry include an analog front-end, consisting of an instrumentation amplifier and a low-pass analog filter (106 Hz cutoff frequency). Digital processing is then carried out by the CC2531 CPU: just after first A/D conversion, digital filtering of mains (50 Hz) frequency noise is carried out. Then the input signal is numerically derived, in order to emphasize Q-wave peaks, the frequency of which is subsequently identified by means of a threshold comparator.

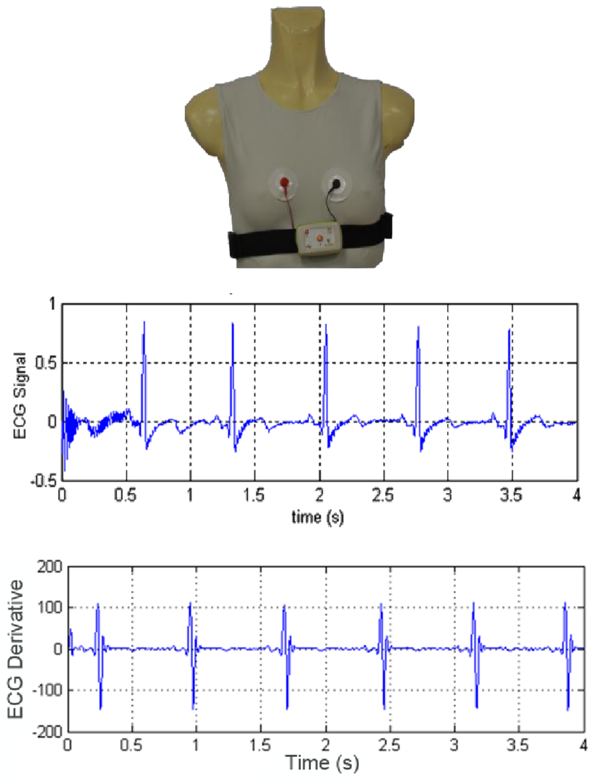

Fig. 5 MuSA embedded ECG subsystem

In order to deal with individual diversity, the algorithm thresholds are automatically calibrated, on the basis of the signal acquired in the early monitoring stages.

TABLE I.
HEARTBEAT RATE ESTIMATION

	Average relative error
Einthoven I lead	4,1955%
Einthoven II lead	2,8221%
Einthoven III lead	2,0008%

The estimated heartbeat rate is then checked against (user-defined) normal range boundaries: should such boundaries be exceeded, an alarm is issued to CARDEA, which, in turn, activates messaging strategies aimed at relatives, medical doctors, neighbors, caregivers, etc., according to the current profile. Since the estimate on moving subject can be quite noisy, the alarm is issued on average estimation. Such an approach is compatible with available computing resources and accurate enough for the given purpose: by computing heartbeat frequency on-board, no ECG tracing needs to be transmitted on the radio-link, thus greatly reducing radio power consumption.

Tests have been conducted on a set of volunteers, under different activity conditions, and exploiting different Einthoven leads: estimated frequencies were then compared with those extracted from a reference instrument. Results are summarized in Table I above, and demonstrate the achievement of fairly reliable detection in all cases.

C. Breathing Rate Detection

Estimation of breathing rate exploits a piezoelectric sensor (Measurement Specialties LDT0-028K) inserted into the elastic chest strap. The sensor detects variations in the strap strain due to inhaling and exhaling movements, and produce a charge variation at the piezo-polymeric film. The signal is hence acquired through a charge preamplifier, having a narrow, low-frequency bandwidth (0.007 Hz - 16 Hz), so to filter out components due to movements different from breathing.

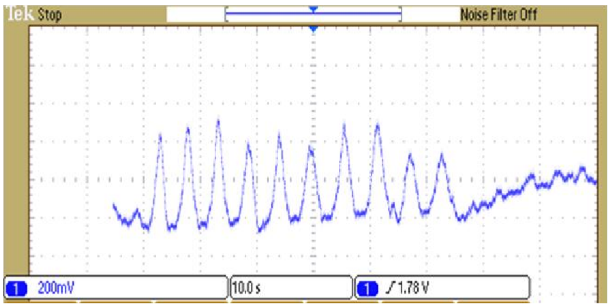

Fig. 6 MuSA embedded breathing-rate estimation subsystem

Similarly to the ECG section, after a further analog amplification stage, the signal (shown in Fig. 6) is acquired by the TI-CC2531 chip, which looks for amplitude peaks. In this case too, the time-domain sensor signal (an example of which is shown in Fig. 4) does not need to be transmitted to CARDEA: MuSA compares breathing frequencies worked out with the assigned "normal" range, and issues anomaly warnings when needed. By exploiting CARDEA cooperation, careful partition of tasks between the wearable device and the environmental infrastructure was made possible, allowing for effective management of the available power and computational budgets. At the base station side, most functions (alarm dispatching and notifications) can be borrowed from environmental control modules, thus resulting in an inexpensive and versatile device. Moreover, data coming from MuSA can be correlated with environmental information sources, to increase, through data fusion, the overall reliability of the monitoring system. Finally, sharing the same CARDEA information space, makes MuSA outcomes readily available on the web, thanks to the CARDEA*web* extension.

Conclusions and Ongoing Work

The concept of multi-sensor, multi-functional wearable platform is being currently expanded, accounting for further functionalities: in particular, MuSA prototypes are being developed including body temperature and microphonic sensors. Body temperature is acquired through a low-cost NTC thermistor, embedded in the chest strap as well. Analog signal treatment is carried out through an instrumentation amplifier (TI-INA330, [6]), whereas digital processing is carried out, as usual, by the CC2531 chip. First tests show that such a low-cost approach still allows for accuracy in the 0.1 °C, which is adequate for long-term monitoring purposes.

Including a microphone will also allow MuSA user to communicate verbally with remote caregivers, when seeking for assistance or in case of fall. Integration with CARDEA avoids the need of accounting for a bi-directional voice-channel: incoming voice message can be managed by the environmental control system, thus not requiring to embed speakers or audio amplifiers info MuSA. A tiny MEMS microphone (Analog Devices ADMP401- 4-5) easily fits the MuSA board. Sampling and digital encoding of the audio stream is carried out by the digital processor, which subsequently send it over the radio link.

CARDEA-MuSA is currently undertaking a field-test campaign, being deployed at some assisted-living facilities already running long-term CARDEA trials [3]. Besides technical performance and reliability, assessed by lab test, this will allow to check its ergonomic and psychological impact on elderly users and on their caregivers, allowing for optimizing the service and to evaluate potential benefit of the adoption of wearable multifunctional devices in actual care policies.

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