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Enhancing the performance of upper limb gesture reconstruction through sensory fusion

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Abstract— **A novel method devoted to the reconstruction of the joint angles in a kinematic chain is described. The reconstruction algorithm is based on the fusion of the information deriving from inertial sensors (accelerometers) and conductive elastomer strain sensors. Accelerometers provide a reliable reconstruction when they are employed as inclinometers in quasi-static conditions. They suffer from artifacts when they are used to detect fast movements or when interactions with the environment occur. The knowledge of the frequency components of the movement to be detected permits removal of these artifacts. Conversely, conductive elastomer sensors have a complex dynamic response, but they can easily provide the frequency content of the movement to be detected. A filtering strategy of the inertial sensor signals based on the elastomer sensor response provides a reliable reconstruction of joint variables during the movement.**

I. Aims

Continuous daily-life monitoring of the functional activities in neurological patients during their physical interaction with the environment is essential for optimal guidance of rehabilitation therapy by medical professionals and coaching of the patient [1]. Such performance information cannot be obtained with present monitoring systems [2]. It is the objective of this paper to introduce an unobtrusive system for monitoring activities of daily life and for training of upper limb motor function in diseased subjects. The system, integrated in clothing (e-textile), includes both fabric-based Conductive Elastomer (CE) and inertial sensors and provides telemonitoring capabilities. CE materials show piezoresistive properties when a deformation is applied [3], [4]. They can be applied to fabrics or to other flexible substrate and they can be employed as strain sensors [5]. These materials represent an excellent trade-off between mechano-electrical transduction and possible textile integration. On the other hand, the construction of a relationship between a fabric strain field and a human position may be difficult and computational expensive. Inertial Measurement Units (IMUs) give an accurate measurement of body movement, but they are bulky, they suffer for magnetic disturbances and they are still quite expensive. IMU measures of body segment orientation are reliable in quasi static situations (from static to mild user activity), while the signal treatment in dynamic cases (from mild to intense activities) requires high computational resources (e.g. the effect of the segment acceleration is a "noise" to be minimized with a complex dynamic filtering). In this paper, a new strategy for arm movement recording is introduced. Upper limb CE sensors detect local deformations on the fabric close to joints, while accelerometers measure the body segments inclinations. A sensory fusion methodology and algorithm are described, leading to enhanced performance in limb gesture reconstruction.

II. Materials and Methods

In the wearable sensing system we developed, the arm movement is estimated by using information coming from both CE sensors and two accelerometers, respectively placed on the arm and the forearm. CE sensor systems can be directly smeared or knitted onto the fabric and can be arranged in different topologies. Thanks to their piezoresistive properties, CE textile sensors are able to measure strain fields. Accelerometer system is able to detect the mutual inclination between two or more frames fixed with sensor elements. While the use as inclinometer is trivial at rest or in rectilinear uniform motion by evaluating the coordinates of $\bar{g}$ in the local accelerometer frames, obtaining the same results in case of movement is more difficult because the sensor measurement is affected by the instantaneous acceleration $\bar{a}$ [6]. To eliminate $\bar{a}$ contribution, a Kalman-based estimator capable of extracting only the $\bar{g}$ components has been developed. Unfortunately this algorithm is not robust with respect to the perturbations induced by the external environment. Data fusion between the two technologies endorses the obtained system with more robustness with respect to perturbations.

A. IMUs, Kalman filtering and $\bar{g}$ component extraction

An accelerometer measures the acceleration and local gravity it experiences. Considering a calibrated triaxial accelerometer (i.e. offset and sensitivity are compensated and the output is expressed in units of $|g|$), the output signal contains two terms and it is given by $\bar{a} - \bar{g}$, where $\bar{g}$ is the component due to the gravity and $\bar{a}$ is due to the system inertial acceleration, both of which are expressed in the accelerometer reference frame. IMUs employed in this work are WID-5 developed by ADATEC srl [7]. The module is provided with a tri-axial accelerometer, a bi-axial gyroscope and a wireless communication unit. The gyroscopic components have not been taken into account for the data fusion with CE sensors. Hereafter, we will generally denote with IMU or inertial sensor only the accelerometric information from the WID-5 module. In static or rectilinear uniform conditions, only the factor due to gravity is present and the inclination of the accelerometer with respect to the vertical is measured. In dynamic conditions, an estimation of the inclination is unreliable only by using the raw accelerometer signal since the inertial acceleration is added to the gravity term. This estimation error gets more important as the sensor undergoes faster movements (for example, during the measurement of a subject in running or jumping). In literature, the inclination is commonly extracted by low-pass filtering the accelerometer signal with a very low cut-off frequency ($< 1Hz$) [8], [9]. In this way, no negligible signal frequency contents are lost and high delays are introduced. To perform a reliable estimation of body segment inclination, a new algorithm based on a Kalman filter [10] was designed and implemented: this technique was described in [11] and it was validated in the detection of operators falls to the ground. Our technique allowed a reliable real time estimation of body inclination even during intense activities.

B. CE strain sensor model and dynamic performances

CE composites show piezoresistive properties when a deformation is applied. They can be integrated into fabric or into other flexible substrate and employed as strain sensors. CE we used is a commercial product by WACKER Ltd (Elastosil LR 3162 A/B) and it consists of a mixture containing graphite and silicon rubber. A complete characterization of the CE quasi-static behavior can be found in [12]. The overall error which comprehend electric noise and low frequency hysteresis, characterizing the measurement is estimated to be 2.5 %. From a dynamic point of view, the non-linear differential model fitting the CE behavior, described in [12], has been modified to account for the following properties :

- i Both in cases of deformations which increase the length of a CE specimen and in cases of deformations which reduce it, two local maxima greater than both the starting value and than the regime value occur.
- ii The amplitude of the overshoot peaks increases with the rate of strain $\dot{l}(t)$.
- iii When the CE is motionless after a solicitation, its resistance versus time can be approximated by a linear combination of exponential functions. The transient time depends on the properties of the sensor and does not depend on the applied stimuli [12].
- iv When the CE specimen undergoes a (fast) periodical stretching, an exponential envelope-trend transient time leading up to a periodical output is observed.

To realize a model able to account for all these phenomena, let us consider the map defined as:

$$g(t) = a_0 + a_1\, l(t) + a_1\, \dot{l}(t) + a_2\, \dot{l}^2(t) \tag{1}$$

where a_0, a_1, a_2 and a_3 are nonzero real numbers depending on the CE properties. Relationship (1) is aimed at modeling the non linearity and the length rate dependence in the sensor behavior described in (i) and (ii). Let us consider now a second-order map which can account for properties (iii) and (iv). In terms of a Laplace transform, it can easily be obtained as:

$$H(s) = \frac{s - \beta_0}{(s - \alpha_0)(s - \alpha_1)} \tag{2}$$

where β_0, α_0 and α_1 are three complex numbers having the real part smaller than 0, and the real part of β_0 is greater than the real parts of the poles α_0 and α_1. In time-domain the complete transfer function, obtained by combining $h(t)$ and $g(t)$, is given by:

$$R(t) = \frac{\alpha_0 e^{\alpha_0 t} - \alpha_1 e^{\alpha_1 t}}{\alpha_0 - \alpha_1} \dot{R}(t_0) + \frac{\alpha_0 \alpha_1 (e^{\alpha_0 t} - e^{\alpha_1 t})}{\alpha_0 - \alpha_1} R(t_0) + \int_{t_0}^{t} \frac{(\alpha_0 - 1)e^{\alpha_0 (t-\tau)} - (\alpha_1 - 1)e^{\alpha_1 (t-\tau)}}{\alpha_0 - \alpha_1} \left(\frac{d\, g(\tau)}{d\tau} - \beta_0 g(\tau) \right) d\tau \tag{3}$$

C. Sensor fusion strategy and CE sensor model improvement

Information deriving from accelerometers used as inclinometers presents the uncertainty described in section II-A, mainly due to the effect of inertial acceleration that the algorithm of gravity extraction is not able to compensate. To assess the accuracy of the accelerometer measurement, several criteria of goodness can be employed. The most used in literature is based on the the Signal Magnitude Area (SMA) index [13]. Inclination extracted from the accelerometer is considered reliable if SMA is smaller than a fixed threshold ϵ which depends on the usage limits. When the SMA index is greater than ϵ the considered sensor is affected by external perturbations which invalidate the measurement. To improve the overall system performances in dynamical conditions, an ad hoc strategy based accelerometer/CE sensory fusion was developed. Accelerometer perturbations, due to environment forces, typically occur as signal spikes (for example during the measurement of the arm movement, if the subject simultaneously walks). For this reason, perturbation frequency components are poorly overlapped with the ones of the movement to be detected. CE sensor signal is computationally expensive to be interpreted for the complexity of the dynamical model describing their behavior and reported in section II-B. On the other hand, CE sensor signal is not affected by inertial acceleration due to external force perturbations, thus its frequency content is highly correlated to the one of the movement to be detected. According to these preliminary remarks, an adaptive accelerometer filtering, has been implemented. The filter has an adaptive bandwidth computed using the signal derived by CE sensors and it constitutes the core of the data fusion. According to this strategy, in figure 1 the procedure aimed at extracting the joint angle of a one-DOF kinematic chain is represented. Two three-axial accelerometers are placed on the bones which match the considered joint and a CE sensor is placed across the joint. The latter sensor undergoes a strain field when the joint flexes. Signals deriving from IMUs and CE are processed as shown in figure 1 and described in the following:

- The blocks KF_i are Kalman-filters that instantaneously transform the signal deriving from IMUs into the three components of $\bar{g}$ evaluated in the frame fixed with the sensor by neglecting the real acceleration $\bar{a}$ and adaptively filter the three signals by using the frequency ω related to the frequency content of the CE signal.

- The rotation $R(\theta)\bar{g}_2$ of the vector $\bar{g}_2$ is performed in order to match the orientation of $\bar{g}_1$ and $\bar{g}_2$ (θ represents the lagrangian coordinate of the joint).
- The error $e(\theta) = \bar{g}_1 - R(\theta)\bar{g}_2$ is computed.
- Starting from $e(\theta)$, a new angle is computed through an iterative procedure. If $e(\theta) = 0$ the old value for θ is held.
- The output θ is used to estimate the length $\bar{l}$ of the CE sensor through a joint model.
- The estimated $\bar{l}$ is used as the fictional output of a Kalman estimator (KfL) whose status is the vector of the CE model parameters. This step is aimed at refining the knowledge of the CE sensor properties, described in equation (3).
- The inverse of the CE model (block M_{CE}^{-1}) is used to extract, through the block $Fr.E.$ the main frequency content ω, used for the accelerometer signal filtering

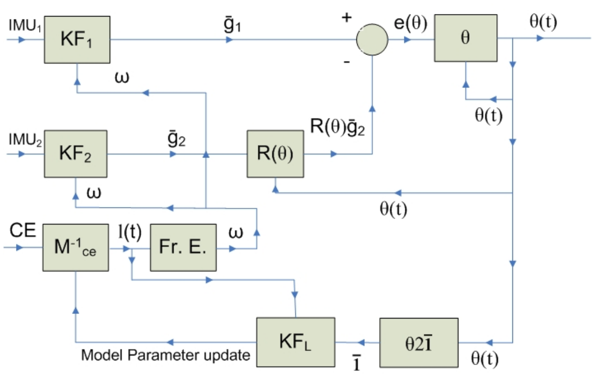

Fig. 1. A functional schema of the data fusion and the CE model upgrade

The blocks M_{CE}^{-1} and $Fr.E.$ operate as follows. CE sensor length $l(t)$ is estimated and its Fast Fourier Transform FFT is computed by block $Fr.E.$. By using the spectrum $L(i\omega)$ of $l(t)$, the frequency ω which realizes the 10% of the spectrum amplitude maximum is determined. ω is then employed to set the parameters of the adaptive filters. To archive this, a Kalman estimator having the CE model parameters as state variables has been implemented in KF_i. In this way, the behavior knowledge of the employed CE sensor is continuously improved by the described feedback.

III. Wearable System for Elbow Movement Detection

The sensory fusion algorithm has been tested on a simple prototype aimed at the reconstruction of the elbow flexion-extension (Fig. 2). The described method has been applied to a subject during walking. Walking induces on IMUs two different types of perturbation in the movement analysis. The first one is due to arm oscillations connected to the gait, while the latter is related to environment forces, such as ground reactions. Two accelerometers have been placed on the posterior side of the forearm, by the distal radial-ulnar joint and on the medial side of the arm, close to the deltoid tuberosity. The two inertial elements have been oriented and calibrated to detect shoulder and elbow movements on the sagittal planes as rotations about the local y axis. A CE strain sensor is placed by the humerus-ulnar joint and complete the sensor system. When the elbow performs a flexion, the CE sensor undergoes a strain. To determine a model for humerus-ulnar joint, used in the block $\theta 2\bar{l}$ described in section II-C, the elbow has been considered as a ginglymus joint with a fixed radius.

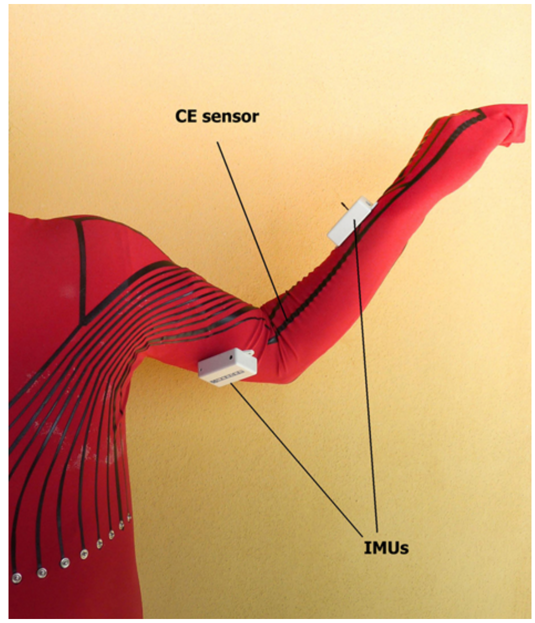

Fig. 2. Sensor placement in the integrated system as described in section III

IV. Experimental Results and Conclusions

This section shows the results of the trial described in section III. In figures 3 and 4 the raw and filtered accelerometer components are plotted. The signal variations on the y axes are related to the gait of the subject.

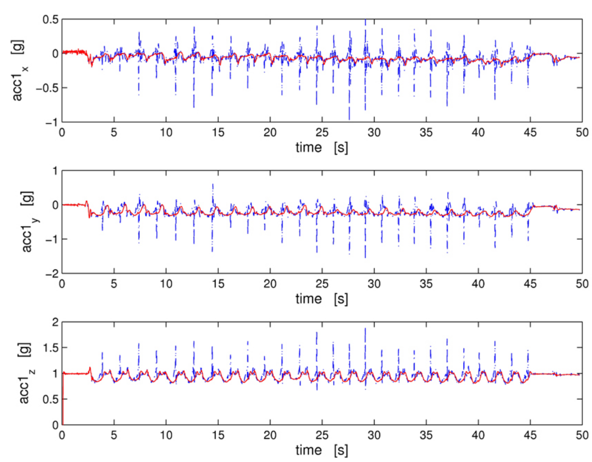

Fig. 3. Acceleration components (in $|g|$-scores Vs. time) deriving from acc_1, placed on the arm. Components are evaluated on the x, y and z axis of the relative frame. The raw data are represented by the blue graphs, the dynamic filtered ones are described by the red charts.

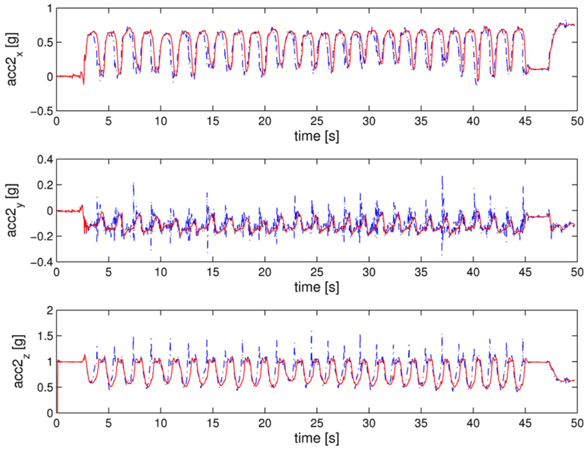

Fig. 4. Acceleration components (in $|g|$-scores Vs. time) deriving from acc_2, placed on the forearm. Components are evaluated on the x, y and z axis of the relative frame. The raw data are represented by the blue graphs, the dynamic filtered ones are described by the red charts.

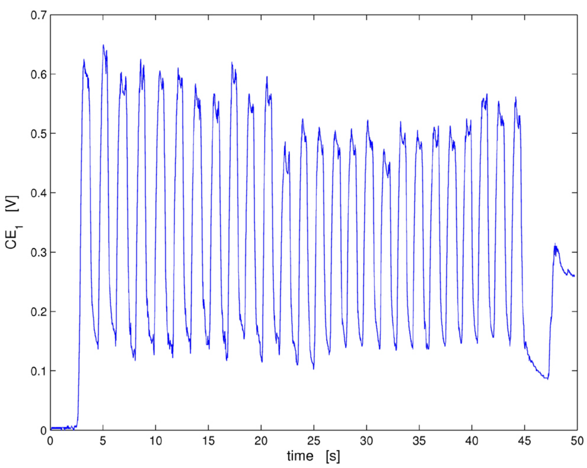

Fig. 5. Signal obtained by the CE sensor (Voltage Vs time), used to determine the filter cutoff frequency

They have the same trend and they are removed by the sum block in figure 1. x and z components of the accelerations contain the information necessary to reconstruct the elbow movement during the experiment. The raw signals deriving from the Kalman estimators of the accelerometers, containing errors due to the interaction with the environment having spike form, are treated by the adaptive filter settled by the CE sensor (reported in figure 5).They are compared to determine the rotation matrix $R(\theta)$ and the searched joint angle θ via an iterative procedure. Finally, in figure 6, a comparison between the joint angle estimated by the sensory fusion and by a commercial electrogoniometer (Biometrics LTD) is showed. The comparison highlights a maximum errors between the two measurement of $5°$, While the root mean square error is of order of magnitude of $1°$.

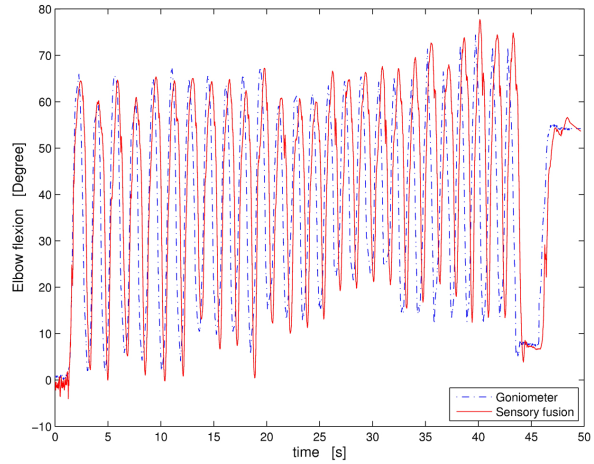

Fig. 6. A comparison between the sensory fusion system response and a the output of a commercial electrogoniometer by Biometrics, placed across the elbow.

V. ACKNOWLEDGMENTS

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