Automatic fall monitoring using the floor vibration

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This work investigated the possibility of monitoring the activity and the fall of people in dwellings using three or more accelerometers fixed on the ground. The main difference with respect to the existing methods is that the acceleration is used to estimate the impact force by using the apparent mass of the floor, experimentally identified in each room where tests were performed using the heel drop test. The study can be divided in three parts: in the first one, the apparent mass of different dwellings’ floors has been measured. Given that the vibration transmissibility was sufficient to measure the vibration generated by the fall at a few meters from the impact location, the second part was the study of the force generated by the fall; the ground reaction force was studied using a purposely designed force platform with a surface of approximately 2 m x 1 m. The force platform allowed measuring the forces generated by the fall of 21 subjects, of a crash test dummy (falling in front or rear direction from seated and standing position, with or without the interposition of objects on the trajectory) and of common objects (dishes, water bottles, books). The impact location was estimated by triangulation using a wavelet algorithm derived from the literature. Results have shown the possibility of identifying the presence of subjects inside the room and the falls in the majority of dwellings; the discrimination of subjects and objects was not an issue, given that the difference in terms of force (that can be estimated from the floor apparent mass and from the measured acceleration) is at least of one order of magnitude.

Section: RESEARCH PAPER

**Keywords:** Vibration, Fall monitoring, Measurements, Assisted Living, Active Ageing

**Citation:** Thomas Bruns, Dirk Röske, Paul P.L. Regtien, Francisco Alegria, Template for an IMEKO event paper, Acta IMEKO, vol. A, no. B, article N, month year, identifier: IMEKO-ACTA-03 (2014)-01-01

**Section Editor:** name, affiliation

**Received** month day, year; **In final form** month day, year; **Published** month year

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**Funding:** This work was supported by a grant from Regione Lombardia (“Avviso pubblico per la realizzazione di progetti di ricerca industriale e sviluppo sperimentale nel settore delle Smart cities and Communities - POR-FESR 2007-2013 asse 1 - Linea di intervento 1.1.1.1. azione E”).

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1. Introduction

The continuous improvement of living standard creates new challenges for humanity: the lifespan expansion of industrial nation’s inhabitants is one of the major burdens of a today’s society health care. Estimations show that by 2050 we could expect the number of elderly persons, living in their own home but requiring assistance, to triple [1]. One of the most hazardous scenarios is fall [1,2]. Approximately 33% (range: 15 to 44.9%) of community-dwelling USA’s elders older than 65 years and up to 60% of nursing home residents fall each year [3-5]. Falls (loss of balance resulting in coming to rest on the floor) are the one of the major causes of death injuries of injury-related hospitalization among senior citizens.

Different works focused on the possibility of detecting the fall using portable systems [5-24]; the majority of the methods rely on wearable sensors [7-10] and vision techniques [11-18]. The main limitation of the wearable systems is that these methods are not effective when the sensor is not worn and elders show a certain hostility versus new technologies and often forget to wear or recharge the sensor. Vision systems might fail in presence of occlusions between the camera and the subject, consequently the experimental setup might be complex if it is necessary to cover the entire house surface. The use of the floor vibration as a diagnosis for the people presence or fall of people inside a room was already exploited in the literature [19-21]. Alwan et al. [19] observed that, as human activities cause measurable vibrations on the floor [25], it is possible to detect human falls by monitoring the vibration patterns. The above hypothesis entails that the vibration signature of the floor differs from that of common daily life activities and from that of falling objects. Authors used piezoelectric accelerometers preloaded against the ground using a mass and spring system. The system included a battery-powered pre-processing electronics, that starting from the measured vibration produced a binary fall signal. Authors performed tests in controlled laboratory environment and concluded that it is possible to detect the fall starting from vibration patterns. The detection range was around 4.5 m on concrete slab floors. Authors claimed that results depend on the floor dynamics, which can be measured with the instrumented heel drop test proposed by Blakeborough and Williams [26], but no further details are reported in the paper. In the standard heel drop test, a subject with mass standing on the balls of his feet, with talons at approximately 8 cm from the ground suddenly relaxed and let the heels fall on the ground.

Litvak et al. [20] and Ziegel et al. [21] proposed an automatic fall detection system based on floor vibration and acoustic noise. A pattern recognition algorithm was used to discriminate between falls and spurious events. Tests for human falls were simulated using a mannequin and were only performed in laboratory environment; to date there is no study comparing the force of dummies and of young subjects. Furthermore, the forces generated by older adults are may be different from those of young subjects because of the limited muscular force and to their reduced mental alertness. The works by Alwan, Allen and Ziegel are very relevant in the field, but did not include analyses on the vibration transmissibility in residential buildings and do not consider that fall against objects or from seated position may result in very low acceleration levels.

In this work, we describe a study for the detection of people’s falls using an estimation of the ground reaction force. The estimation is performed by measuring floor vibration by accelerometers attached to the floor and by characterizing the floor apparent mass and the vibration transmissibility before starting the measurements. Preliminary tests for the discrimination between falls of objects and subjects were performed by using a purposely designed force platform. In addition to the validation of the method, this paper investigates:

* the transmissibility of vibration in different residential floors, that have never been studied in the literature. Given that the fall generally occurs at variable distances from the sensors, it is necessary to identify the vibration transmissibility in order to assess building‑dependent modifications of the signal;
* the force generated by people fall have been studied for frontal falls and rear falls of young healthy subjects [27-29];

The paper is structured as follows: the proposed method is described in section 2; section 3 describes the experiments performed in laboratory (falls of crash test dummy, athletes and objects), in dwellings (identification of vibration transmissibility) and in real conditions. Results are discussed in section 4 and the paper conclusions are drawn in section 5.

1. MATERIALS AND METHODS

The detection of subjects’ fall using the floor vibration measured on the ground is influenced by three phenomena: the vibration is modified by the floor transmissibility, the force generated by the impact is unknown, and there may be other events leading to vibration signals that might be similar to that deriving from people’s fall.

The proposed approach is summarized in Figure 1: the vibration transmissibility through the different grounds and the force generated from the different impacts are studied separately in order to be able to predict the vibration generated by different falls on the different floors. In other words, with the separate characterization of the force generated by an impact on an infinitely rigid floor and of the vibration transmissibility through the floor it will be possible to understand a variety of combinations between impact locations, fall type and floor characteristics. The estimated force signals will be used in future works as training phase for the algorithms for the event detection, similarly to what was done in references [30-32].



Figure 1 Scheme of the proposed method

* 1. **Proposed** **method**

The dependence between the fall impact force and the measured floor vibration is constrained by the ground mechanical impedance, which is the ratio between the force and the velocity, or by the ground apparent mass, i.e. the ratio between the force and the acceleration [33-36]. If the behaviour of the ground is linear, both the apparent mass and the impedance can be estimated with impact tests similar to those described in ref. [26]. The ground apparent mass (AM) can be therefore estimated at low frequencies with the heel drop test, by knowing the force generated by the heel (*F*) and the acceleration (*a*) measured at a position *j* when the heel drop test was performed at a location *i*.

$AM\_{i,j}\left(f\right)=\frac{F\_{i}\left(f\right)}{a\_{j}\left(f\right)}$

Given that this quantity is constant (if the ground behaviour is linear), if the subject falls close to the location *i*, it is possible to estimate the force generated by the fall by multiplying the apparent mass of the ground AM*­i,j(f)* times the measured acceleration during the real fall at the position *j*.

$F\_{i,fall}\left(f\right)=AM\_{i,j}\left(f\right)∙a\_{j,fall}\left(f\right)$

With this method, it is possible to classify the fall events using the force instead of the acceleration as used in all the existing methods required in the literature. The proposed approach requires the knowledge of the impact location that, in our case, was identified using the wavelet method described in references [37]. The method requires positioning at least three triaxial accelerometers on the ground in order to detect the plate longitudinal waves. The continuous-wavelet transform, using the Gabor function as mother wavelet as suggested in ref. [37], was used to identify the time of arrival of the waves to the different sensors. At each frequency, the time difference between the first arrivals to two sensors is related to the so-called wave group velocity through the known distance between two sensors. The group velocity *Cg(f)* was therefore computed as the ratio between the distance L and the difference between the times of arrival t1(f) and t2(f) computed from the wavelet scalogram at the frequency f.

$C\_{g}\left(f\right)=\frac{L}{t\_{2}\left(f\right)-t\_{1}(f)}$

In this study, the time arrival was evaluated by analysing only the fastest propagation mode identified by the scalogram maxima.

Once that the location of the impact was identified, the force time history is finally then computed using the inverse Fourier transform of equation (2).

* 1. Ground Transmissibility

The impact on the ground generates compressive and flexural waves that propagate through the floor from the impact position to the sensors’ location. The subjects’ fall can be identified by observing different features of the signal (in either time or frequency domain) and by using information about the impact location (to discard, for instance, shocks occurring in specific positions). The first step for the feasibility study is the identification of the floor vibration transmissibility in residential buildings, given that if the transmissibility tends to zero, it will not be possible to measure the vibration also at small distances from the impact location. Therefore, we have decided to analyse a group of houses with different characteristics in order to evaluate the possibility of locating the transducers in positions that are not critical for the daily activities of people.

Since the vibration transmissibility depends on the mechanical and geometrical characteristics of the base and of the floor, experiments were performed in different conditions. For current purposes, four IEPE accelerometers model Bruel&Kjaer 4508 B, with nominal sensitivity of 10 mV/(m/s2) measured the vibration at the positions indicated in Figure 2.



**Figure 2** Position of the accelerometers and of the impact in the transmissibility tests.

Three accelerometers (indicated with the asterisk in the figure) were fixed at positions that depended on the room dimensions (a longer room side, b shorter room side). Another accelerometer was moved close to the impact location. The vibration signals were sampled using a National Instruments NI 9234 data acquisition board. The sampling frequency was 2048 Hz. The stimulus was given by the force generated in a heel drop test. The subject that did the tests also performed the same tests on the instrumented platform described in section 2.3 (20 tests performed in repeatability conditions), in order to obtain the average excitation force together with its variability (standard uncertainty 13% in our tests).

The vibration transmissibility and the ground apparent mass was measured in 40 rooms, with surfaces between 2 and 50 m², with different floor materials (wood, stones, tiles). Experimental results have been summarized by averaging the vibration transmissibility of different buildings. The latter was measured using the H1 estimator of the frequency response function, by averaging the results of 5 tests (lasting 2 s with a pre-trigger of 0.3 s). The ordinary coherence function has been computed as well.

* 1. Measurement of the Ground Reaction Force

Given that the proposed method is based on the computation of the ground reaction force (hereinafter GRF), we have designed a force platform with a surface large enough to perform fall tests. The platform was built with a sandwich honeycomb panel (2.5 x 1.25 m) supported by four piezoelectric load cells PCB 211B. The sandwich thickness is 100 mm, with sheets thickness of 1 mm and honeycomb thickness of 50 m. The upper sandwich layer was covered by 5 mm thick compensated wood in order to protect the surface from the localized impacts generated by the dummy. The theoretical computations pointed out a resonance frequency of approximately 85 Hz. The dynamic behaviour of the force platform has been experimentally verified with an impact hammer and outlined that the frequency pass-band (±3dB) was 40 Hz; the first natural frequency of the unloaded plate was 63 Hz. Also in this case, data were pre-triggered so that the first impact of the object with the platform occurred after 0.3 s.

Three groups of simulations were performed:

* Fall simulations performed by subjects falling forward and backward with complete fall arrest: tests are performed on the force platform by 21 healthy young subjects with height between 1.65 and 2.00 m and body mass between 45 and 95 kg (average 72 kg). Subjects were instructed on how to perform the simulation to avoid injuries; tests were performed in accordance with the ethical guidelines of Politecnico di Milano; the tests differed because of:
	+ Direction of Fall: Front Fall (F) or Rear Fall (R)
	+ Subject Body Mass [kg]
	+ Subject height [m]
	+ Hip height [m]
* Fall simulation performed by a dummy (Humanetics pedestrian dummy, Hybrid III 50th Percentile, mass 104 kg) was used to identify the force excided by different fall configurations. Simulations were performed without or with limited fall arrest according to the following configuration
	+ Type of Fall: Rear, Front or Side
	+ Pre-fall posture: Standing or Sitting
	+ Height of the hips before fall: 0.5, 0.6, 0.7 or 0.8 m
	+ Limbs arrest posture: no arrest, one arm arrest, two arms arrest and elbow arrest
	+ Distance between the feet before the fall: 0.2 or 0.3 m
	+ Description of fall trajectory: free trajectory or fall over the objects
* Falls of common objects of different weight, size, and shape from different heights:
	+ Objects: plastic bottle, glass, glass bottle, dish, pot or box
	+ Object weight
	+ Height of the fall: 0.7 or 1.4 m
	+ Number of falling objects

During the experiments, both the acceleration and the GRFs were recorded. Data were summarized using basic descriptive statistics. The ratio between the average mass of the subjects that performed the test and the mass of the dummy is 0.7, consequently also the GRF should be in a similar proportion if the fall configuration is similar.

Not all the possible combinations between factors were included, given that part of them was meaningless: for instance, it is almost impossible in a frontal fall to have an elbow impact; only the realistic fall configurations were reproduced and analysed.

* 1. Method validation

The proposed method for the localization of the fall using wavelets and for the computation of the force has been validated in two steps. The first validation was performed on the force platform: the expected vibration of the sensor was computed using equation (2) using the location of the impact (estimated using the wavelet triangulation) and the force measured by the load cells. The expected vibration has been compared with the acceleration measured at different locations. The difference between the estimated and the measured acceleration of all the tests was used in order to assess the method reliability.

In the second step, an embedded system, based on MEMS accelerometers and Raspberry PI board, was installed in a residential building and the vibration was monitored inside a small bath and in the bedroom. The rooms were characterized using the method described in section 2.1. The tests aimed at the validation of the architecture and at the possibility of detecting common activity of daily living.

1. Results
	1. Method validation

The method has been validated by comparing the acceleration measured on the force platform with that predicted using the measured GRF and the apparent mass of the force platform itself. Figure 3 shows an example of the comparison in one of the tests performed by with the crash test dummy.



Figure 3 Force signal (upper plot), measured vibration (black line) and expected vibrations (red line) (middle plot) and the test error (lower plot)

Results, apart from a tonal component at the resonant frequency of the plate not reduced by the digital filtering of data, shows maximum errors lower than 20%. Because of the system linearity, the error is the same for the estimation of acceleration during the method validation (by knowing the GRF) or for the estimation of the force during the real tests (by measuring the acceleration and the floor characteristics).

The average error on the magnitude of the first acceleration peak (evaluated on the entire data set) is 23%. The error is due to the difficulty in the identification of the location of the impact, that in approximately 50% of cases resulted in the choice of a point close to the one where the impact occurred. In addition, the apparent mass of the plate was measured without the mass of the dummy/subject, thus leading to a biased compensation of the FRF. This aspect was confirmed by the spectral analysis of the error, that was dominated by components at frequencies between 55 and 63 Hz. These values are close to the first natural frequency of the platform and vary between different tests depending on the position of the subject/object.

The average error (Figure 4) decreased to 16% when the accelerations were computed on falls of subjects and crash test dummy (i.e. excluding the objects, where the measured forces were characterized by a poor SNR). In these conditions, the error on the magnitude of the largest acceleration/force peak decreased to 14%; the average error, apart from the force peak, was lower than 5%. Also in this case, the spectral analysis evidenced the dominance of frequency components close to the first resonance of the platform.



Figure 4: Average difference between the measured and the predicted acceleration generated by the falls of dummy and subjects.

* 1. Ground Transmissibility

The average vibration transmissibility measured in 40 rooms is shown in Figure 5 a and the average coherence between the input and output position (asterisks and circles in Figure 2) is shown in Figure 5 b. Plots include the effect of the different rooms’ sizes, of the floor mechanical characteristics and of the different positions of the impact and of the sensors.



**Figure 5** Averaged transmissibility of the room that underwent to our tests (a) and average coherence of the transmissibility tests (b). Solid line: test average, dotted line maxima and minima measured during the tests.

The plots show that the modulus of the vibration transmissibility is averagely lower than 1 in the band between 0 and 150 Hz. The average transmissibility has a minimum below 15 Hz, but the lower value (0.3) does not prevent the measurements in that region. The coherence is averagely larger between 20 and 50 Hz; this interval represents the one in which the SISO system approximation is more reasonable. At lower frequencies the effect of non-measured inputs (such as the vibration of the building induced by natural agents or by the traffic) might be relevant. Above 50 Hz, the lack of energy in the stimulus might lead to low Signal to Noise ratio. Further analyses evidenced that the vibration transmissibility and the coherence function depend on the floor type and on the room size: the transmissibility measured on the wooden floors is averagely lower than that on the tiles and stones, especially at high frequencies. As expected, the first resonance frequency depends on the room size, while the effect of the furniture is negligible in comparison with the effects of floor type and room size. Three examples of the effects of the room properties on the coherence and transmissibility are shown in Figures 6, 7 and 8.



**Figure 6** Influence of floor covers on signal transmissibility: floors covered by tiles (solid line) and by parquet (dashed line)



**Figure 7** Influence of room size on the signals coherence: small sized rooms (solid line), middle sized (dashed line) and big sized rooms (dotted line)



**Figure 8** Influence of room sides ratio a/b on measured signals coherence: if ratio a/b higher than 2 (solid line), if ratio a/b lower than 2 (dashed line)

 Figure 6 shows that the transmissibility of the vibration with the parquet is smaller, on average, than the vibration transmissibly when the floor is covered with tiles. The average transmissibility between 1 and 150 Hz with the tiles was 0.54; the value dropped to 0.26 when the floor was covered by the parquet.

A similar effect was noticed for the room size, where the vibration transmissibility of small rooms (0.55 between 1 and 150 Hz) was averagely larger than that of large rooms (0.38 in the same frequency range); the coherence between the stimulus (force) and the response (acceleration), shown in Figure 7, was independent from the room size between 15 and 50 Hz (0.87, 0.89 and 0.87 for large, medium and small rooms respectively) At higher frequencies (100 to 150 Hz), the coherence measured in large rooms (0.61) was smaller than that of medium (0.70) and small rooms (0.79), reasonably because of the lower signal to noise ratio when the accelerometer is far from the impact location.

The effect of the ratio between the room dimensions was small on both the transmissibility and coherence (Figure 8); the average coherence at frequencies between 15 and 50 Hz was 0.88 independently from the room sides’ ratio. Between 100 and 150 Hz, the average coherence was 0.76 for rooms with a side ratio lower than 2 and 0.84 for rooms with the ratio higher than 2.

* 1. Impact force

The averaged GRF measured during the fall of the dummy, of the healthy subjects and of the objects is shown in Figure 9.

Results evidence that the force generated by the dummy is, on average, much larger than that generated by objects and healthy subjects. This is partially due to the larger mass of the Humanetics dummy in comparison with the average subjects’ masses. The ratio between maximum force averagely generated by the fall of a dummy (close to 10 kN) and the maximum force generated by the fall of a subject (approximately 1 kN) is 10, i.e much bigger than the ratio between the masses (1.4). This large difference can be explained by two factors: the first is that the dummy does not have any conscious reaction to the fall; this aspect is typical of elders, that usually do not protect themselves using the arms. The second factor is the difference between the biomechanical characteristics of the crash test dummy and the subjects; this factor is expected to be limited, given that the dummy is designed in order to mimic the behaviour of subjects exposed to impulsive accelerations.



Figure 9: Time histories of the GRF measured during the dummy falls (a), objects falls (b) and healthy subjects falls (c). Solid lines: averages, dotted lines: maximum and minimum.

The comparison between the average GRFs and the average accelerations generated by the falls of objects, subjects and dummies is shown in Figure 10.



Figure 10: Comparison between averaged GRF and acceleration signals obtained during dummy, subjects and objects falls

The frequency content of the fall of subjects and objects is usually different, as shown by the wavelet transforms of Figure 11. The plot show that the impact of hard objects (part b) creates vibration at higher frequencies (over 70 Hz) while the bandwidth of acceleration generated by the impact of a soft object (paper box, part a) is lower than 35 Hz. As a comparison, the spectrum measured during the fall of the dummy is reported in part C of Figure 11.



Figure 11 Wavelet Transforms of accelerations signals excided by falls of a soft object (a), an hard object (b) and the crash test dummy (c).

The possibility of distinguishing between the falls of objects and people is confirmed by the wavelet transforms of the average GRF measured during all the tests (shown in Figure 12). Differently from the falls of objects, the GRF has relevant components also at low frequencies. The dominating frequency components of observed during the falls of objects is close to 15 Hz, while the dominating frequency components of falls generated by subjects are typically below 5 Hz.



Figure 12 Wavelet Transforms of the average of the objects GRF (a), subjects GRF (b) and dummy GRF (c)

Another characteristic that allow distinguishing the fall of objects from that of subjects is the number of impacts. The fall of both subjects (b) and dummy (c) usually generate two spectral peaks (impact of two body parts, such as knees and hands or elbows and head) while the fall of objects usually generate a single spectral peak.

* 1. Preliminary experimental results

The last step of the research was the installation of the embedded measurement system in a residential building. To date, there were no falls and consequently it was not possible to validate the fall detection system or to obtain real fall data. Nevertheless, results showed that the system detects the activities of daily living, showing vibration levels much large than the floor noise during the day.

1. Discussion

Results presented in this paper evidenced the compatibility between the frequency of the fall-generated excitations and the frequency region in which the vibration transmissibility is high. The vibration transmissibility is suggesting that it is possible to measure the vibration at any position of the room, independently on the impact location, so theoretically one accelerometer is enough for detecting the presence of people in the room or their fall. The simultaneous use of at least three transducers, however, allows identifying the location of the fall and consequently allows the estimation of the GRF that has generated the vibration. This parameter is, in principle, more reliable than the vibration generated by the fall, which depends on both the event that has generated the fall and on the distance between the impact location and the transducer.

The uncertainty of the GRF is limited by the heel drop test used for the identification of the ground apparent mass. From this perspective, we have already performed tests by dropping a silicone ball from a constant height; results are by far more repeatable and will be presented in future studies.

The force generated by the fall of subjects is larger than that generated by the fall of objects, and the identification of a threshold is, in principle, easier than the identification of threshold for the acceleration level, that depends both on the impact magnitude and on the position of the fall with respect to the accelerometer. The identification of thresholds was not included in this work and is deserved to forthcoming studies, in which we will try to use the techniques proposed in ref. [23,32] using the force instead of the acceleration as the main feature for the recognition.

Results showed that the use of three accelerometers allow estimating the location of the fall, although in approximately 50% of laboratory falls, the impact location was identified at a point adjacent to the actual one (error lower than 1 m). The optimal transducer location will be studied in forthcoming studies, but thanks to the low cost of the MEMS accelerometers, it seems reasonable to put more than three sensors in each room in order to obtain a more reliable impact position estimation.

The main limitation of this work is surely the lack of an experimental validation in real condition. During the scheduled experimental activities in residential buildings for elders, there were no falls and consequently it was not possible to verify the proposed method. Nevertheless, results of the tests performed in laboratory conditions were promising and we expect to obtain more data in future experimental sessions.

1. Conclusions

In this paper, we have described a method for the detection of people fall in dwellings that uses the ground reaction force as a main parameter for the event classification. The method is based on the identification of the floor apparent mass using the heel drop test and on the computation of the impact location using at least three triaxial accelerometers. The method was validated on a purposely-designed force platform; fall simulation tests were performed with a crash test dummy, and young healthy subjects. The force generated by the fall of objects was also measured as a term of comparison. Given that there is an order of magnitude between the GRF generated by the fall of objects and subjects, the parameter should be more reliable than the acceleration.

Tests were also performed to identify the apparent mass and the vibration transmissibility of common residential buildings. Results evidenced that the transmissibility is larger than 0.3 up to 150 Hz, thus showing that the vibration generated by the fall (that has a bandwidth close to 40 Hz) can be transmitted inside the room and therefore measured by the different accelerometers.

Preliminary tests were not useful for the method validation, given that there were no falls during measurements. The future developments will include new series of tests in residential buildings, a more reliable method for the measurement of the apparent mass of the ground and the simultaneous usage of more accelerometers in order to improve the localization accuracy.

Acknowledgements

The authors wish to thank all partners of the project (www.smarta-project.it) and specifically: Datamed S.r.l., Flextronics Design S.r.l., Argonet S.r.l., Software Team S.r.l., Electron, Dipartimento di Informatica UNIMI, Dipartimento di Design of Politecnico di Milano and CoDeBri. This work was financially supported by a grant from Regione Lombardia (“Avviso pubblico per la realizzazione di progetti di ricerca industriale e sviluppo sperimentale nel settore delle Smart cities and Communities - POR-FESR 2007-2013 asse 1 - Linea di intervento 1.1.1.1. azione E”).

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