Sturzerkennung in mobilen Geräten

Fall Detection in mobile Applications

Dosch Probabilistic Density Model (DPDM)
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DOSCH&AMAND Lösungen für Smart Home Telecare
Produkt DA1432 indePendant™ mit DPDM

DOSCH&AMAND Solutions for Smart Home Telecare
Product DA1432 indePendant™ with DPDM

Zielvorgabe und Aufgabenstellung

Moderne Telekommunikation muß in Zukunft auch die Bedürfnisse älterer und hilfebedürftiger Menschen unterstützen. Hierzu gehören vor allem diejenigen Menschen, die alleinstehend sind und weiterhin in ihrem gewohnten Zuhause verbringen wollen und können, wenn ihnen entsprechende Hilfsmittel zur Verfügung stehen würden.

Jedermann bekannt ist der „rote Knopf", mit dem ein Alarm ausgelöst werden kann. Dies ist zwar ein Ansatz für die besagte Problemstellung, aber keine hinreichende Lösung. Es fehlen u.a sofortige verbale Kontaktaufnahme mit der Notrufstelle, Hilferufsequenzen an Freunde und Nachbarschaft, Kontaktbewahrung mit Family&Friends, Erinnerungsfunktionen, aber vor allem der automatische Notruf im Falle eines Sturzes.

Eine zuverläßige Sturzerkennung, die in mobile Endgeräte (Mobiles) integriert werden kann, gibt es heute noch nicht mit der erforderlichen Qualität bzw Zuverläßigkeit. Diese „always-on"-Funktion darf vor allem die Standzeit der Batterie nicht wesentlich reduzieren und muß mit moderater Rechenleistung und Speicherbedarf auskommen. Die bisherigen mathematischen Modelle wie KFD über Merkmalsextraktion im Hilbertraum sind viel zu aufwendig für die Integration in Mobiles. Überdies liefern die KFD Diskriminanten keine ausreichend zuverläßige Erkennung des Ereignisses „Sturz" in seiner ganzen Vielfältigkeit

Gesucht ist also ein mathematisches Modell und sein numerischer Algorithmus, der im Rahmen der technischen Rahmenbedingungen eines Mobiles integrierbar ist und zuverläßig „Sturz" erkennt. Dies ist mit dem neuartigen DPDM-Verfahren erstmals gelungen. DPDM wurde in das DECT Mobile DA1432 indePendant™ integriert und mit Erfolg in zahlreichen Feldtests erprobt.

Zu Stromverbrauch: Die thermische Leistung eines DECT Endgerät im Ruhemodus (ohne NEMO und ULE) beträgt typisch 5mA. Bei einer Batteriekapazität von 450mAh (Standardklasse Li-Ion) kann dieses Endgerät ca 3 Tage (10% Reserve) ohne Nachladen betriebsbereit bleiben. Wenn dieser Standby-Wert nicht signifikant reduziert werden soll, darf die Sturzerkennung nicht mehr als typisch 1% der thermischen Grundbilanz verbrauchen. Das bedeuted, daß der zusätzliche mittlere Stromverbrauch durch die Sturzerkennung maximal 50µA betragen darf. Das wären in 3 Tagen 350µAh, also 1% der Ladekapazität der Batterie inkl. der besagten Reserve. Die detaillierten Daten des DPDM-Verfahrens sind am Ende des Aufsatzes zu finden.

Introduction

In near future modern-style telekommunication must also meet the necessities of elderly and handicapped people. For example, solutions are requested for elderly persons who want to live at home even if they are alone. In principle this is possible if adequate auxiliary means are available and utilisable.

Well-known the „red button" which can be pressed for executing alarm to a professional service center. Although a pure alarm button is a basic way of looking at this problem, it is not an adequate nor a sufficient solution. Missing features are instant verbal contact to emergency contact, maintaining the contact with family&friends, reminder functions and most notably, a reliable Fall Detection with automatic alarm handling.

Up to now a reliable Fall Detection integrated in Telecommunication Mobiles is not available, at least not with necessary quality and trustworthiness. Fall Detection as always-on-function must not reduce the battery's standby time and must be executed with moderate processor performance and memory. The classics as KFD (Kernel-Fisher-Discriminates) which use extraction of properties via Hilbert space are by far to complex and computational intensive for being integrated in the limited available environment of a mobile device. Moreover KFD discriminates do not deliver reliable verdicts "fall detected" in the face of diversity of falls

Wanted: Mathematical model and its numeric algorithm which can be integrated in mobile devices (DECT, GSM/LTE) with ultra low power consumption, but even so can work and detect "falls" reliably. The recently developed DPDM method can be such candidate. DPDM has been integrated into DECT device DA1432 indPendant™ and subject to numerous field trials. The results have been promising.

regarding Power Consumption: In IDLE mode the thermal Amps consumption of a DECT device is typically 5mA. Assumed a Li-Ion battery supplies 450mAh, this device can stay alive for ca 3 days including 10% reserve to avoid deep discharge. If such standby time should not be significantly reduced, an applicable Fall Detection must not take more than 1% of idle mode consumption which means 50µA in average or 350µAh within 3 days. Please read the technical details of the DPDM method at the end of this essay.

Why methods as KFD cannot solve this problem

The essential task in the requested data processing is to separate two disjoint, finite subsets X_j and X_k of a Euclidean space R^m through a hypersurface $H \subset R^m$ whereas in our problem X_j shall represent "no fall" subset and X_k "fall" subset. KFD comes into favor for solving this problem as it has the flexibility of a nonparametric model using kernel mixture, while its implementation algorithm uses a parametric notion via kernel machine. The KFD has been emerging from the machine learning community and can be linked to classical results of discrimination of Gaussian processes in Hilbert space.

What is the fundamental fragmentariness of KFD as an algorithm for binary classifications : Based on historical data a prediction process must be calibrated (conditioned, learn mode). For new data values, a KFD process shall be capable to predict, if they belong to class X_j or X_k. This principle however requires that calibration data must be comprehensive enough to extract respective features for a reliable projection pursuit. In other words: How voluminous and representative must be the calibration data for "fall detection" to deliver a reliable best likelyhood estimate for "fall detection"? In practice of fall detection, such calibrations are always imperfect in the face of diversity of falls.

How does KFD work mathematically (Kernel Fisher Discriminant) ?

References: (1), (2), (3)

A Fisher linear discriminant is a vector ω that maximizes

$$J(\omega) = \frac{w^T S_B w}{w^T S_M w}$$

where the between-class and within-class scatter matrices are defined by

$$S_B = \sum_{c}^{n} \left(N_c (\mu_c - \mu)(\mu_c - \mu)^T \right) \quad \text{and} \quad S_M = \sum_{c}^{n} * \sum_{i>c}^{m} \left((x_i - \mu_c)(x_i - \mu_c)^T \right)$$

Where μ is the mean of the x_i and μ_c is the mean of the x_i within class c.

The matrix S_B defines the data of a feature space which must be generated as data set from fall detection calibaration space. The limits of the most likelyhood estimations is defined by the fact that S_B will always be imperfect in fall detection data space.

It is commonly known that linear discriminants are not complex enough to separate data sets effectively. To deal with nonlinear separations, we consider a mapping Φ from sample space into X a feature space F . Assuming that the Fisher linear discriminant ω in F can be expressed as a linear combination of sample points in F, this requires

$$\omega = \sum_{i=1}^{m} \left(a_i \, \phi \, (X_i) \right)$$

In terms of α , the objective function ***J***(α) now reads

$$J(\alpha) = \frac{a^T \phi S_B \, a}{a^T \phi S_M \, a}$$

The between-class scatter is now given by

$$(\phi\, S_B) = (M_1\text{-}M_2)(M_1\text{-}M_2)^T \quad \text{with} \quad (M_i)_j = 1/l_j \sum_{i>c}^{m} < \phi(x_j), \phi(x^j{}_k)>$$

Where M_i is a vector of length $l = l_1 + l_2$ and $< \phi(x_j), \phi(x_k)>$ represents the inner product between data points in the new feature space ***F*** which represents the data points of the predicted fall detected.

The within-class scatter is given by

$$(\phi\, S_M) = K_1\,(I - I_1)K_1^T + K_2\,(I - I_2)K_2^T \quad \text{with} \quad K_i = (< \phi(x_j), \phi(x^j{}_k)>)$$

Where I_{li} is a matrix with all entries set to $1/l_j$ and K_i is a matrix of inner products in feature space of dimensions $(l \times l_i)$.

The computation of

$$J(\alpha) = \frac{a^T \phi S_B \, a}{a^T \phi S_M \, a}$$

needs complex matrix operation for

$$(\phi\, S_B) = (M_1\text{-}M_2)(M_1\text{-}M_2)^T \quad \text{and} \quad (M_i)_j = 1/l_j \sum_{i>c}^{m} < \phi(x_j), \phi(x^j{}_k)>$$

$$(\phi\, S_M) = K_1\,(I - I_1)K_1^T + K_2\,(I - I_2)K_2^T \quad \text{and} \quad K_i = (< \phi(x_j), \phi(x^j{}_k)>)$$

for all events triggered by a data source e.g. acceleration sensor. A precondition is the representative matrix K_i for the feature space which means the learning extracts of fall events. This overvall complexity could not be implemented in a standard DECT device as DA1432 indePendant™ without adding dedicated processor chipset with MathLab performance capability and adequate memory space. Such technical approach would also violate the target for minimal power consumption of max 50µA. Moreover the computation of

$$J(\alpha) = \frac{a^T \phi S_B \, a}{a^T \phi S_M \, a}$$

would always be imperfect due to a non-consistent feature space K_i . The conclusion is: KFD is a non-desirable effort for non-ideal results regarding fall detection in mobile devices.

Therefore KFD principles have not been considered for DA1432 indePendant™, but a dedicated new method which has been named DPDM

Let's use a different approach which also applies a best-likelyhood estimation but based on terms of probabilistic density model and full data integrity with respect to any applicable event.

Dosch Probabilistic Density Model (DPDM)

A) Fundamentals

The DPDM approach has learned a lesson from Kernel Prediction Models: Find a mathematical model with data space integrity ! This sounds quite irrealistic, but DPDM will show, it is not. We have learned from KFD that the data space matrix

(0) $$\{\Phi S_M\} = K_1\,(I - I_1)K_1^T + K_2\,(I - I_2)K_2^T$$

will always be incomplete with respect to the enormous variety and diversity of fall events as training data space for KFD most likelyhood estimation.

DPDM will use a data space for predicted fall detection $\{\Phi S_M\}$

(1) $$\{\Phi S_P\} + \{\Phi S_M\} + \{\Phi S_D\} + \{\Phi S_U\} = \{\Phi \mathfrak{E}\} = 1$$ ("1" => means: data integrity !)

(2) $$\{\Phi S_M\} = |1 - \{\Phi S_P\} + \{\Phi S_D\} + \{\Phi S_U\}|$$

$\{\Phi S_M\}$ is the prediction of "fall detected" based on data space integrity. This is the major advantage compared to kernel prediction models based on imperfect conditioning datas for the identical data space.

B) Processing tri-axial acceleration data

The outputs of a tri-axial accelerometer are

(3) $$\left\{(s_x)^k = \sum_{k=0}^{n} s_x\,\boldsymbol{\Delta} t_k\right\} \left\{(s_y)^k = \sum_{k=0}^{n} s_y\,\boldsymbol{\Delta} t_k\right\} \left\{(s_z)^k = \sum_{k=0}^{n} s_z\,\boldsymbol{\Delta} t_k\right\}$$

for axis x, y, z

and $k = 1 \ldots n$ where n is the number of samples

and $\boldsymbol{\Delta} t_k = \boldsymbol{\Delta} t$ = const = 5ms (sampling rate for given tri-axial sensor chipset)

(more technical details about applied HW is available at the end of this essay)

The range of values for s_x, x_y, s_z are

$s_{x,min} = s_{y\,min} = s_{z\,min} = 0$

$s_{x,max} = s_{y\,max} = s_{z\,max} = +/-16$ (relevant to applied technology and setup)

The device is in IDLE state if

$s_x = s_y = 0$ and $s_z = 1 = g_0 = g/g_e$ whereas $g_e = 9{,}81\ m/s^2$

or following (4) and (5) below : $\left\{(\acute{S})^k = (\acute{S})^{k_2}\right\} = 1$ in IDLE state

The device is in free fall if

$s_{x,}$ = s_y = 0 and s_z = 0

or following (4) and (5) below : $\left\{(\acute{S})^{k} = (\acute{S})^{k_2}\right\}$ = 0 in FREE FALL state

A sampling rate of 5ms has shown to deliver sufficient time-axis resolution for DPDM approach. In fall or close-to-fall events the direction of the mobile device can change in inpredictable manner. Some fall-detection methods try to extract informations from such turns but in fact these informations deliver more ambiguities than convergencies for reliable verdicts regarding fall detection. In DPDM there is no need to compute with vectors (amplitude,angle) but it is sufficient to calculate with scalars whereas it is important not to miss any data from all three axes.

We can easily eliminate all direction-relevant datas by geometric addition:

(4) $$\left\{(\acute{S})^{k_2} = \sqrt{((\acute{s}_x \boldsymbol{\Delta} t_k)^2 + (\acute{s}_y \boldsymbol{\Delta} t_k)^2 + (\acute{s}_z \boldsymbol{\Delta} t_k)^2)}\right\}$$

The result is a scalar representing the total acceleration which has an impact on the device. We will see that we can dispense with square root as the quadratic transformation delivers even a better separation of datas close ***S=0*** and close to ***S=1***, because

(5) $$\left\{(\acute{S})^{k} = (\acute{S})^{k_2}\right\}$$ for S^k = 0 and S^k = 1 (!)

Therefore we will use further-on

(6) $$\left\{(\acute{S})^{k} = (\acute{s}_x \boldsymbol{\Delta} t_k)^2 + (\acute{s}_y \boldsymbol{\Delta} t_k)^2 + (\acute{s}_z \boldsymbol{\Delta} t_k)^2)\right\}$$

How to calculate $\{\Phi S_P\}$ $\{\Phi S_D\}$ and $\{\Phi S_U\}$? We know from (2) that if we subtract them all from $\{\Phi\mathfrak{E}\} = 1$, we will get a complete data space for $\{\Phi S_M\}$ representing "fall detected" as prediction data space.

If we compare $\{\Phi S_M\}$ with KFD we can approximately say

(7) $\{\Phi S_M\}_{\text{KDF}} \approx \{\Phi S_M\}_{\text{DPDM}} = \{\Phi S_M\}$

as $\{\Phi S_M\}_{\text{DPDM}}$ is based on a data space integrity compared to $\{\Phi S_M\}_{\text{KDF}}$ which is not.

The data spaces are related to

$\{\Phi S_P\}$ probability density matrix for data space **p**roduct fall

$\{\Phi S_D\}$ probability density matrix for data space **d**aily life

$\{\Phi S_U\}$ probability density matrix for data space **u**nnormal movement

C) Elimination of time dependancy from $\left\{(\acute{S})^k = (\acute{S})^{k_2}\right\}$

The time-wise evaluation of a tri-axis data set is one of the most relevant characteristic which deliver an indefinite number of different fall events. Therefore many experimental results recommend pre- and post-analysis (later often called "Postures") around the assumed fall event in order get to more associations of a "real fall" or a "false fall". All these approaches stay imperfect in the face of the enormous variety of time-relevant characteristics.

DPDM eliminates the time dependancy of all data events. It its therefore irrelevant for the subsequent DPDM prediction if a fall is composed by several sections of fall datas. This is substantial advantage as moreover it significantly reduces the data $\{\Phi S_P\}\{\Phi S_D\}$ and $\{\Phi S_U\}$

All Δt_k elements of $\{\Phi S_P\}$ $\{\Phi S_D\}$ and $\{\Phi S_U\}$ will be eliminated applying following transformations

(8) $$(S_P)_H{}^n = \sum_{k=0}^{n} k \sum_{\acute{S}=0}^{1-\boldsymbol{\delta}} (\acute{S})^k \boldsymbol{\Delta} t_k + \sum_{k=0}^{n} k \sum_{\acute{S}=1+\boldsymbol{\delta}}^{S_{max}} (\acute{S})^k \boldsymbol{\Delta} t_k$$

for $\acute{S} \neq 1 \geq 0$
$\boldsymbol{\delta} = (s_{min} + s_1{}^H)/2$
$k = \boldsymbol{\delta}/10 \; .... \; \boldsymbol{\delta}/2$

(9) $$(S_D)_H{}^n = \sum_{k=0}^{n} k \sum_{\acute{S}=1-\boldsymbol{\lambda}+\boldsymbol{\delta}}^{1+\boldsymbol{\lambda}-\boldsymbol{\delta}} (\acute{S})^k \boldsymbol{\Delta} t_k$$

for $\acute{S} \neq 1 \geq 0$
$\boldsymbol{\lambda} = (1 + s_{max})/2$

(10) $$(S_U)_H{}^n = \sum_{k=0}^{n} k \sum_{\acute{S}=1-\boldsymbol{\lambda}}^{1+\boldsymbol{\lambda}} (\acute{S})^k \boldsymbol{\Delta} t_k - \sum_{k=0}^{n} k \sum_{\acute{S}=1-\boldsymbol{\lambda}+\boldsymbol{\delta}}^{1+\boldsymbol{\lambda}-\boldsymbol{\delta}} (\acute{S})^k \boldsymbol{\Delta} t_k$$

which can be iteratively calculated by

(11) $$(S_U)_H{}^n = \sum_{k=0}^{n} k \sum_{\acute{S}=1-\boldsymbol{\lambda}}^{1+\boldsymbol{\lambda}} (\acute{S})^k \boldsymbol{\Delta} t_k - (S_D)_H{}^n$$

The data spaces of $(S_P)_H{}^n$ $(S_D)_H{}^n$ and $(S_U)_H{}^n$ do not contain any time-relevant parameter:

(12) $(S_P)_H{}^n = n_m(\acute{S}_p)^m = (S_P(s_n))_H{}^n$ whereas $\boldsymbol{n_m}$ = resolution of $\acute{S}$ (e.g. $\boldsymbol{n_m} = \delta/2$)

(13) $(S_D)_H{}^n = n_m(\acute{S}_D)^m = (S_D(s_n))_H{}^n$

(14) $(S_U)_H{}^n = n_m(\acute{S}_U)^m = (S_U(s_n))_H{}^n$

Now we are one step before getting the wanted probability densities for the total data space.

All we have to do is to integrate $(S_P)_H{}^n$ $(S_U)_H{}^n$ $(S_D)_H{}^n$ and exit the process when we have found the maximum sector for a discriminate of best-likelyhood projection for fall detection:

(15) $\{\Phi S_P\} = 1 - \int_{s_n=0+\delta}^{s_n=1-\psi_{Pmax}} (S_P(s_n))_H{}^n \, ds_n$ ψ_{Pmax} = maximize $(\psi_F(|\Phi S_F - \Phi S_P|)/\Phi S_P)$ = $\text{discrim}_{best}(S_P)$

$\{\Phi S_P\}$ range 0 ..... 1-δ

(16) $\{\Phi S_D\} = \int_{s_n=1-\lambda+\psi_D}^{s_n=1+\lambda-\psi_{Dmax}} (S_D(s_n))_H{}^n \, ds_n$ ψ_{Dmax} = maximize $(\psi_D(|\Phi S_F - \Phi S_D|)/\Phi S_D)$ = $\text{discrim}_{best}(S_D)$

$\{\Phi S_D\}$ range 1 ..... 0+λ

(17) $\{\Phi S_U\} = \int_{s_n=1-\lambda+\delta+\psi_U}^{s_n=1+\lambda-\delta-\psi_{Umax}} (S_U(s_n))_H{}^n \, ds_n$ ψ_{Umax} = maximize $(\psi_U(|\Phi S_F - \Phi S_U|)/\Phi S_U)$ = $\text{discrim}_{best}(S_U)$

$\{\Phi S_U\}$ range 1 ..... 0+λ+δ

Finally we have found a best prediction for “fall event” according equation (2)

(2) $\{\Phi S_M\} = |1 - \{\Phi S_P\} + \{\Phi S_D\} + \{\Phi S_U\}|$

and we can easily calculate the extreme states

a) device in **IDLE State**
we know from (3) $\left\{(\acute{S})^k = (\acute{S})^{k_2} = 1 = idle\ state\right\}$

in (15) $\{\Phi S_P\}$ = 1-(1) =0 in (16) $\{\Phi S_D\}$ = 1 in (17) $\{\Phi S_U\}$ = 1

into equation (2) $\{\Phi S_M\}$ = |1-0-1-1 | = 1

b) device in **FREE FALL State**
we know from (3) $\left\{(\acute{S})^k = (\acute{S})^{k_2} = 0 = free\ fall\right\}$

in (15) $\{\Phi S_P\}$ = 1-(0) =1 in (16) $\{\Phi S_D\}$ = 0 in (17) $\{\Phi S_U\}$ = 0

into equation (2) $\{\Phi S_M\}$ = |1-1-0-0 | = 0 and we can finally make decision

(18a) $\{\Phi S_M\} > (0 + \delta) < 1$ „fall section“

(18b) $\{\Phi S_M\} \geq (1 + \lambda)$ „no fall section“

Conclusion

DPDM is a new mathematical approach for fall detection. As KFD (Kernel Fisher Discriminant) DPDM is based on most-likelyhood prediction but its prediction is based on data integrity for fall discrimination and not on imperfect conditioning datas for the identical data space. Therefore DPDM is insensitive towards the enormous diversity of fall events because DPDM's probability density model completes all fall events as missing parts for data integrity.

The DPDM method delivers high sensitivity towards falls but avoids "false alarm"even for close-to-fall events. A further but major advantage of DPAM is its ultra low power consumption of average 50µAh which qualifies "always-on-DPDM" for mobile applications. This is possible in combination with ultra-low-power 3D/6D-axis sensor technology (e.g. STM LIS3DH @ 2µA) and a mathematical algorithm which can reliably evaluate fall events without any further assisting data sources (e.g. barometer) and post-event measures.

DPDM Fall Detection has been integrated into DA1432 DECT independent™ and subject to lab and field trials. First results delivered promising results. The trials will be intensified in 1Q2018. DA1432 will be available for OEM partners and B2B agreements end of 1Q2018. It is expected that DPDM feature will significantly upgrade the security and independancy of elderly people at home.

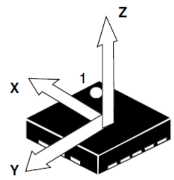
DECT indePendant ™ DA1432

DA1432 is the daily assistant for elderly persons with maximum simplified MMI and inambiguos way of use, perfected for people with special needs. Beside Fall Detection, DA1432 is a one-button communication link to family & friends, a help-call-sequencer to predefined buddy list, a reminder to taking medikaments and the central control of Smart Home elements (smoke detector, door entry, temperature,…). Simple use and event associated voice announcements in native spoken languages are basic features of DA1432.

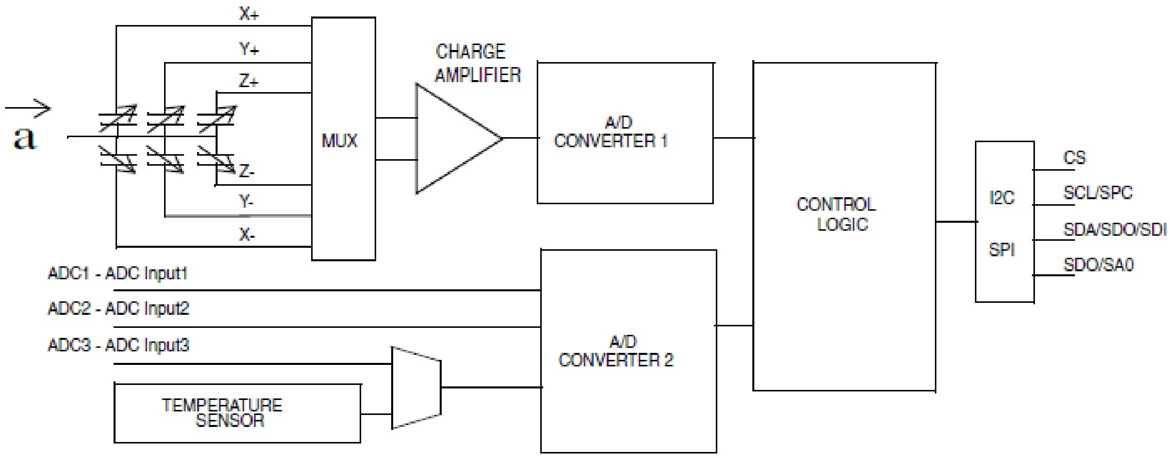
DA1432 is available from DOSCH&AMAND Products GmbH in OEM design.

D) Technical Datas (Hardware)

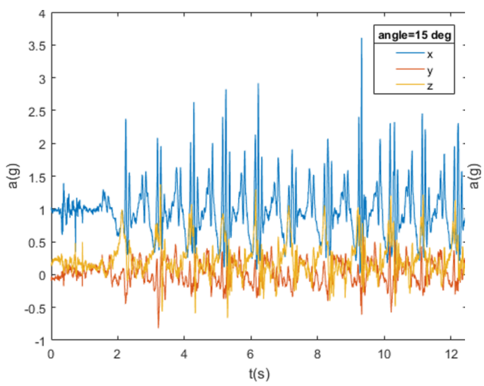
DECT Hardware	DCX79 and DCX81	DSP Group
DECT Software	DECT GAP stack	DOSCH&AMAND
3-axes accelerometer	LIS3DH	STMicroelectronics Group
LIS3DH (chipset)	power consumption	2 µA
	g-scale (x,y,z)	+/- 2,4,8,16
	output data rate	1 Hz .... 5 kHz
	data resolution	16 bit
	data output	I^2C or SPI
	micro packaging	3*3*1 (mm)
DPDM FALL DETECTION	Firmware on DCX chip	DOSCH&AMAND
	processor	ARM7 core

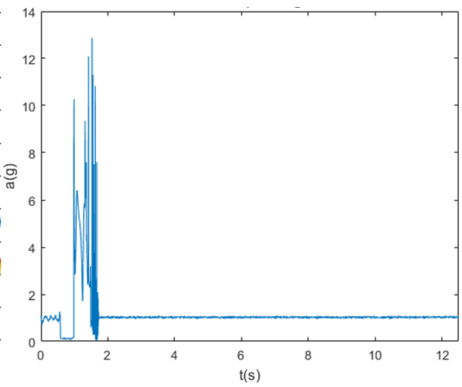


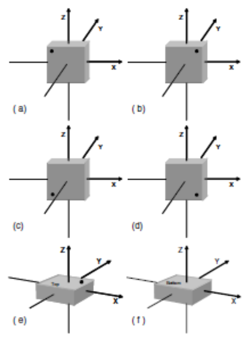
BLOCK DIAGRAM tri-axial sensor technology



D) processed tri-axial data x,y,z (examples walk and fall)







$$\left\{(s_x)^k = \sum_{k=0}^{n} s_x \boldsymbol{\Delta} t_k\right\} \quad \left\{(s_y)^k = \sum_{k=0}^{n} s_y \boldsymbol{\Delta} t_k\right\} \quad \left\{(s_z)^k = \sum_{k=0}^{n} s_z \boldsymbol{\Delta} t_k\right\}$$

$$\left\{(\acute{S})^{k_2} = \sqrt{((\acute{s}_x \boldsymbol{\Delta} t_k)^2 + (\acute{s}_y \boldsymbol{\Delta} t_k)^2 + (\acute{s}_z \boldsymbol{\Delta} t_k)^2)}\right\}$$

6D movement recognition

Author: Dr. Franz A Dosch, CEO of DOSCH&AMAND

Dosch has been Executive Vice President of ROHDE&SCHWARZ and Co-founder of DOSCH&AMAND. He has been intensively involved in the standardisation of GSM and DECT. Dosch has invented ETSI Standard DPRS (DECT Packet Radio Service) whose transport layer “long slot” is today’s DECT Standard for HDVoice. In the 80ies Dosch became well-kown due for his numeric algorithm to simulate electronic circuit design. His time-domain analysis of vRLC circuitries has been implemented in CAD Analysis programs as SuperSpice, AnaCraft, a.o.

DOSCH AMAND RESEARCH DOSCH AMAND PRODUCTS

A major focus of DOSCH&AMAND is Smart Home Telecare with turnkey design (Hardware + Software) of wireless personal assistant (DA1432 indePendant) and its OEM production in China. The concept shall enable a better life for elderly or handicapped people who want to stay at home but are predominantly alone. DA1432 is a first step into this challenging market. Besides the described Fall Detection, DA1432 shall maintain the contact to family&friends, execute help and emergency call sequences, support daily life with reminder functions and finally give a feeling of self-worth because of an independent live at home. Medium term the DA1432 concept will be amended with Smart Home Elements for AAL (Ambient Assisted Living).

Further solutions of DOSCH&AMAND a.o. DECT Repeater, DECT SAT Repeater for e.g. T-COM Speedport, DECT cordless Plug, large scale DECT multicell networks,…

References:

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