A METHOD OF DISTRIBUTED DATA FUSION BASED ON ORTHOGONAL WAVELETS

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Abstract: *Within the last decade, acquiring distributed signals from the same source and then aggregating them into a single signal has captured the interest of many scientists. The first goal of this communication is to introduce and provide a succinct description of VISA – a versatile interface of signal acquisition. Moreover, signals are spatially distributed. The interface is intended to become the kernel of a mobile system allowing the user to perform monitoring of some phenomena. As a second goal, the problem of information compaction by data fusion is also approached within the paper. Wavelets seemingly are suitable tools for extraction of common features from various signals and to compact them into a fused signal. Therefore, a method of data fusion based on orthogonal (Daubechies) wavelets, iterative deepening approach (from Artificial Intelligence) and some statistical criteria is briefly described as well.*

Keywords**:** *data fusion, orthogonal wavelets, radio transmission.*

1. INTRODUCTION

Entities that are able to provide several signals at the same time, in different spatial positions can easily be found. Take for example a simple bearing, integrated into a mechanical system, for which fault diagnosis is performed with the help of vibrations. Usually, there are at least two vibration signals, acquired along orthogonal axes. A more complex application comes from ecology. Signals like soil temperature, humidity or pollution have to be acquired by using a distributed array of sensors, over some geographical area. Signals as such enter the main processing tool through an acquisition interface.

Fig. 1 displays a modern structure of a mobile system devoted to distributed signal acquisition and processing [1]. There are three levels. The low level includes sensors, which are grouped into specialized packets, depending on the signals nature; a generated signal can also be added, if necessary (for systems identification purpose). The inner level is the kernel of the entire system and includes one or more VISA modules. At the high level, signals are processed by means of a laptop, after being transferred through a bus, according to some communication protocol. In this context, *signal processing* stands for a collection of algorithms aiming to implement several methods of filtering, denoising [2], identification [3], prediction [4], diagnosis [5], etc., depending on the application. In this context, the data fusion methods [6] are classed as denoising techniques.

Beside this short introduction, the communication includes 3 more sections. The next one is a briefing on the VISA structure. Section III describes the principle of data denoising and introduces a method based on Daubechies wavelets [7].

Simulation results on vibration data and some insights are exhibited in section IV. The concluding remarks and a short references list complete the communication.

2. VISA STRUCTURE AND FUNCTIONALITY

Focus on the kernel of Fig. 1 – the VISA module. Its structure is illustrated in Fig. 2 and includes several interface modules, such as: acquisition module (for signals coming from sensors), primary processing module (filters), signals generator (for identification applications), communication module (for signals transmission), energy management unit, etc. The modules are organized around a microcontroller that plays the major role in coordinating the interface functioning. Obviously, this hardware structure is completed by adequate software programs.

The microcontroller integrates into a single chip a general use microprocessor, memory units (for programs and data), as well as peripheral ports. In case of VISA, an 8-bit microcontroller from 8051 family has been selected: ADUC832 [8]. Two reasons led to this choice. Firstly, this microcontroller is one of the fewest that includes a 12-bit analog-to-digital converter. Secondly, two digital-to-analog converters are available, which is quite unusual in the configuration of a microcontroller. The two converters simplified the interfacing with sensors. The analog inputs module is receiving electrical intensity signals in range 4-20 mA. Subsequently, signals are adapted to the input of analog-to-digital converter. Adaptation consists of conversion from electrical intensity to potential and preliminary analogical filtering, in order to attenuate aliasing.
Data communication has to fulfill some basic requirements: minimum number of electrical connections; up to 100 m range of information transmission; high protection against perturbations. Therefore, a two-wire bus has been preferred in this aim. The communication is semi-duplex type. Thus, while one device is transmitting information, all the others are either passive or receivers. Data are transmitted by using the serial, asynchronous interface of the microcontroller.

The radio (wireless) communication is an alternative to be considered whenever cables are difficult to install. This communication mode can be implemented by means of a radio transceiver with the following characteristics: radio bandwidth without license; up to 100 m range; at least 9600 bps speed; low energy consumption; stand by mode; easy to interface with the microcontroller; low cost. Such a transceiver is for example BIM2A-434-64 [9].

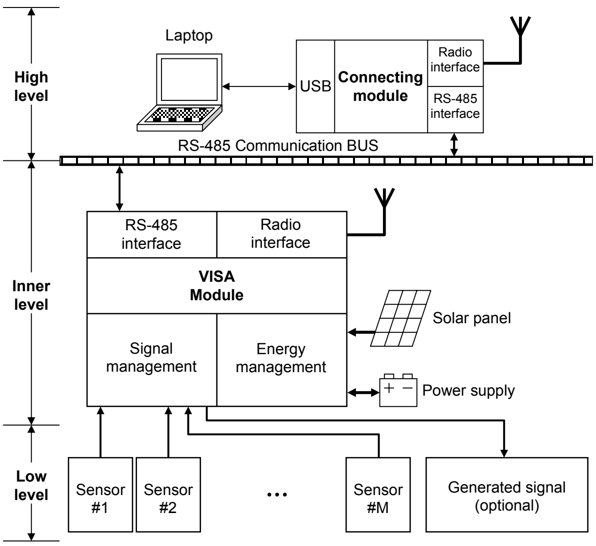

Fig. 1. Structure of a mobile unit for signal acqusition and processing.

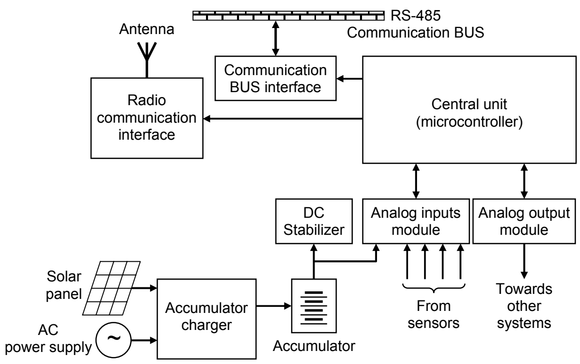

Fig. 2. Structure of VISA module.

Only the main components of VISA have been shortly explained above. In [1], all components are described in depth. The versatility is given by the fact the interface can support a variable number of sensors of different types and, moreover, is independent on the high level processing unit.

3. DATA FUSION BY USING ORTHOGONAL WAVELETS

Assume VISA provides M signals x_1, x_2, ..., x_M, which are acquired from the same source, at the same time, but with spatially distributed sensors. Signals could have different sampling rates. In this case, they are represented with different resolutions. (Shall the signals have the same sampling rate, they are represented with the same resolution.) The data fusion problem is then to aggregate the M signals into a unique signal, x, according to some procedure [10]. Usually, the procedure is designed by accounting some criterion, which allows the user to compare each other all the $M+1$ signals and to declare that x is *the best*. Traditionally, the fusion criteria are subjective. For example, in case of images or audio signals, *the quality* of fused signal should be superior to any of the other signals. An expert is required to assess the quality and, therefore, the criteria could only be subjective. However, in case of signals that cannot be understood by simply transferring them to the brain through the human perceptive system, (like e.g. mechanical vibrations) quality criteria are meaningless. In this case, numerical optimization criteria have to be used.

The *Least Squares Method* (LSM) [3] can lead to a fusion signal of minimum quadratic error. More specific, the signal results after minimization of cost function below:

$$\mathbf{V}(x) = \frac{1}{M}\sum_{m=1}^{M}\frac{1}{N_m}\sum_{n=1}^{N_m}\left(x_m[n] - \hat{x}_m[n\,|\,x]\right)^2 , \quad (1)$$

where: N_m is the number of samples acquired for signal x_m, and $\hat{x}_m[n\,|\,x]$ is a version of x, after being sampled at the same rate as x_m ($m \in \overline{1,M}$). Thus, x is *the closest* signal to any of the other M signals. Practically, x acts like an interpolator for any of the M signals. By minimization of criterion (1), the best interpolator has to be found. The direct use of LSM has a major caveat: it requires the prior knowledge of $\hat{x}_m[n\,|\,x]$ models class. So, x is not the global best fused signal, but rather the best one within some class.

To improve the utility of LSM, statistical criteria can be combined with. For example, the following statistical parameters can be used: *root mean square* (RMS), *crest factor* (CF), *impulse factor* (IF), *clearance factor* (CLF), *shape factor* (SF), *Kurtosis* ($\mathbf{K}$). They quantify some shape characteristics of any digital waveform x of length N and are defined as below:

$$RMS(x) = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(x[n]-\overline{x}\right)^2}\,;\; CF(x) = \frac{\Delta x}{RMS(x)}\,;$$
$$IF(x) = \frac{\Delta x}{\overline{|x|}}\,;\quad CLF(x) = \frac{\Delta x}{\frac{1}{N}\left(\sum_{n=1}^{N}\sqrt{|x[n]|}\right)^2}\,;$$
$$SF(x) = \frac{RMS(x)}{\overline{|x|}}\,;\quad \mathbf{K}(x) = \frac{\frac{1}{N}\sum_{n=1}^{N}\left(x[n]-\overline{x}\right)^4}{RMS^4(x)}\,. \quad (2)$$

Definitions (2) rely on *peak-to-valley* Δx and *mean* $\overline{x}$:

$$\Delta x = \frac{1}{2}\left[\max_{n\in\overline{1,N}}\{x[n]\} - \min_{n\in\overline{1,N}}\{x[n]\}\right];\; \overline{x} = \frac{1}{N}\sum_{n=1}^{N}x[n]\,. \quad (3)$$

To complete the landscape, two more parameters can be added (not necessarily statistical): energy ($\mathbf{E}$) and entropy ($\mathbf{H}$). By definition,

$$\mathbf{E}(x) = \sum_{n=1}^{N}|x[n]|^2 \quad\text{and}\quad \mathbf{H}(x) = -\sum_{n=1}^{N}\frac{|x[n]|}{\mathbf{E}(x)}\log_2\frac{|x[n]|}{\mathbf{E}(x)}\,. \quad (4)$$

While the energy shows how strong the signal is, the entropy has several meanings. In context of data fusion, $\mathbf{H}$ means redundancy: low/high entropy – high/low redundancy.

Let $\mathbf{S}$ be any of the 10 parameters above. Then the best fused signal (i.e. with the best shape characteristics) can be obtained by minimization of the following quadratic criterion:

$$\mathbf{V}(x) = \frac{1}{M}\sum_{m=1}^{M}\left[\mathbf{S}(x_m) - \mathbf{S}(x)\right]^2 . \quad (5)$$

Assume henceforward that the cost function $\mathbf{V}$ is preset and, moreover, that it has no negative values. Then, one can start to design the fusion method. Since the resolution of distributed signals can vary, it is natural to place them within the framework of Multi-resolution Theory devised by S. Mallat, I. Daubechies and Y. Meyer (especially) in [11] and [7]. The basic instruments of a multi-resolution structure that endows the usual signals space (i.e. stable, with finite energy) are the orthogonal wavelets of Daubechies class [7]. The manner in which signals can be represented with the help of the multi-resolution structure is shortly explained next. Then, the fusion method can easier be understood.

According to [11] and [7], any usual, real valued signal f can be decomposed into a finite collection of *details* g_1, g_2, …, g_L, of decreasing resolution, down to some rough approximation f_L:

$$f \equiv g_1 + g_2 + \cdots + g_L + f_L\,, \tag{6}$$

where $L \in \mathbb{N}^*$ is the index of the coarsest resolution. By convention, any detail g_l is a signal of resolution 2^{1-l} (for $l \in \overline{1,L}$), while the resolution of f_L is 2^{-L}. The signals of expansion (6) are evaluated when projecting f onto the multi-resolution subspaces spawn by scaled and time shifted wavelets (see [11], [7]). More specific, let $\{\phi, \psi\}$ be a couple father-mother wavelets of Daubechies class (orthogonal and compactly supported). Then the signals of (6) are linear combinations like below:

$$g_l \equiv \sum_{n\in\mathbf{D}_l} d_{l,n}\psi_{l,n}\,, \qquad \forall\, l \in \overline{1,L} \qquad \text{and}$$

$$f_L \equiv \sum_{n\in\mathbf{C}_L} c_{L,n}\phi_{L,n}\,, \tag{7}$$

where $\mathbf{D}_l \subset \mathbb{Z}$ (for $l \in \overline{1,L}$) and $\mathbf{C}_L \subset \mathbb{Z}$ are finite sets of integers, defined by the support lengths of initial signal f and wavelets $\{\phi, \psi\}$, whereas $\{d_{l,n}\}_{n\in\mathbf{D}_l} \subset \mathbb{R}$ (for $l \in \overline{1,L}$) and $\{c_{L,n}\}_{n\in\mathbf{C}_L} \subset \mathbb{R}$ are wavelet coefficients. By definition, the coefficients are evaluated by projection of signal onto the wavelet subspaces:

$$d_{l,n} = \langle f, \psi_{l,n}\rangle, \quad \forall\, n \in \mathbf{D}_l,\ \forall\, l \in \overline{1,L}\,; \tag{8}$$

$$c_{L,n} = \langle f, \phi_{L,n}\rangle, \quad \forall\, n \in \mathbf{C}_L\,. \tag{9}$$

In equations (7)-(9), the spanning wavelets are generated by applying scaling of factor 2 and time shifting with steps adapted to the current scale:

$$\psi_{l,n}(t) = \sqrt{2^{-l}}\,\psi\left(2^{-l}(t-n)\right), \qquad \forall\, n \in \mathbf{D}_l\,,$$
$$\forall\, l \in \overline{1,L}\,, \tag{10}$$

$$\phi_{L,n}(t) = \sqrt{2^{-L}}\,\phi\left(2^{-L}(t-n)\right), \quad \forall\, n \in \mathbf{C}_L\,, \tag{11}$$

where $t \in \mathbb{R}$ is the continuous time.

In practice, direct implementation of definitions (8) and (9), in order to evaluate wavelet coefficients, is not efficient. Mallat Algorithm [11] is used instead. This allows their evaluation by means of a *Quadratic Mirror Filters* (QMF) bank, as illustrated in Fig. 3.

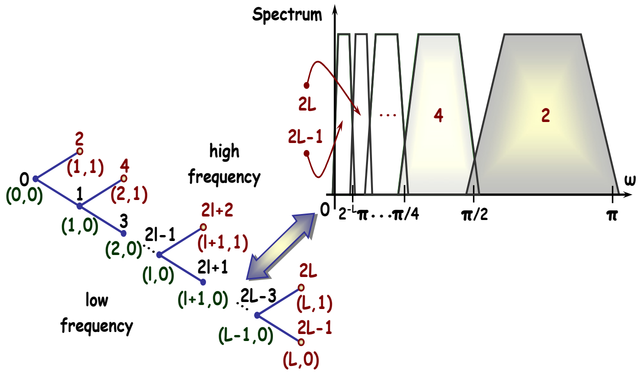

Fig. 3. Principle of Mallat Algorithm.

The binary tree is only a simplified representation of QMF bank. On each couple of arcs (the *elementary cell* of bank), two QMF $\{\tilde{h}, \tilde{g}\}$ lie. Each filter impulse response is uniquely determined by the father and mother wavelets. After filtering, decimation by factor 2 is performed, as Fig. 4 displays below.

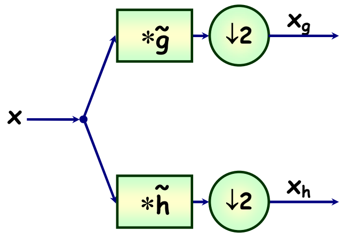

Fig. 4. Elementary cell of a QMF bank.

When transitioning the cell, any discrete signal x, represented with some resolution, is transformed in two signals x_h and x_g, with twice smaller resolution. Moreover, the spectra of resulted signals are complementary: x_h basically encode now the low frequency information of x, while x_g is focusing on the high frequency information. Thus, two effects are produced by the filtering-decimation cell (according to Uncertainty Principle): reduction of time resolution twice and increase of frequency resolution twice as well (by splitting in two the frequency band of input signal). The global frequency effect is illustrated by the right side of Fig. 3, where one can see that any low frequency sub-band is divided in two. Moreover, the frequency configuration is uniquely determined by the coarsest resolution index L. Mallat Algorithm succeeds thus to focus on the low frequency zone of analyzed signal, by means of wavelets. The depth of binary tree is controlling the rough resolution of representation, which cannot be lowered.

The QMF bank is directly employed to compute the wavelet coefficients, if inputted by the initial coefficients set $\left\{c_{0,n}\right\}_{n\in\mathbf{C}_0} \subset \mathbb{R}$. To compute such coefficients, the signal is simply projected on time shifted father wavelets:

$$c_{0,n} = \left\langle f, \phi_{0,n} \right\rangle, \quad \forall\, n \in \mathbf{C}_0 . \tag{12}$$

Each leaf of the tree is thus returning a set of coefficients at some resolution. On the high frequency leaves (2, 4, ..., $2L$), the coefficients sets d_1, d_2, …, d_L are found, while the low frequency leaf ($2L-1$) provides the set c_L. It can be proven that the QMF bank has a supplementary fortunate property: the values of sampled wavelets (10) and (11) can also be returned by its leaves, when starting form a sampled father wavelet. If the initial signal is discrete and not continuous time, it suffices to sample the father wavelet with a corresponding rate, in order to compute the projections (12). Expansions (6)-(7) can thus be exploited to change the discrete signal by interpolation (with wavelets) and re-sampling at a desired rate. Note that re-sampling applies to wavelets and not directly to the initial signal.

Any signal of collection { x_1, x_2, ..., x_M } has to be represented like in (6), depending on its initial resolution. More specific,

$$x_m \equiv y_{m,l_m} + y_{m,l_m+1} + \cdots + y_{m,L} + x_{m,L}, \; \forall\, m \in \overline{1,M}, \tag{13}$$

where the initial resolution index, $l_m \in \mathbb{N}^*$, is set by accounting the signal duration N_m (as indirect measure of resolution). The coarsest resolution index, $L \in \mathbb{N}^*$, is defined by the most refined signal of collection (i.e. sampled at the highest rate), for which $l_m = 1$. Normally,

$$\max_{m\in\overline{1,M}} \left\{l_m\right\} \le L \le \left\lfloor \log_2 \left(\max_{m\in\overline{1,M}} \left\{N_m\right\} \right) \right\rfloor . \tag{14}$$

Expansions (13) can be expressed in a simplified manner:

$$x_m \equiv y_{m,1} + y_{m,2} + \cdots + y_{m,L} + x_{m,L},$$
$$\forall\, m \in \overline{1,M}, \tag{15}$$

where $y_{m,1} \equiv y_{m,2} \equiv \cdots \equiv y_{m,l_m-1} \equiv 0$, $\forall\, m \in \overline{1,M}$.

Let $T_0 > 0$ be the sampling period of the most refined signal and denote by N_0 the number of its samples. Then all signals with sampling periods superior to T_0 can be over-sampled by means of expansion (15). More specific, the re-sampled details of each signal x_m ($m \in \overline{1,M}$), as well as the rough approximation, are expressed as follows:

$$y_{m,l}[k] \equiv \sqrt{2^{-l}} \sum_{n\in\mathbf{D}_{m,l}} d_{m,l,n} \psi\left(2^{-l}\left(kT_0 - n\right)\right)$$
$$\forall\, l \in \overline{1,L}, \tag{16}$$

$$x_{m,L}[k] \equiv \sqrt{2^{-L}} \sum_{n\in\mathbf{C}_{m,l}} c_{m,l,n} \phi\left(2^{-L}\left(kT_0 - n\right)\right), \tag{17}$$

for any $k \in \overline{0, N_0 - 1}$. Hence, all wavelet representations have the same sampling rate (the biggest one). Nevertheless, a different sampling rate could also be employed, if necessary. In this case, some signals would be under-sampled. Note that the resolution of a signal is a subtle concept, not solely determined by the sampling rate. Even though the re-sampled versions of the M signals have the same sampling rate, they continue to preserve the initial resolutions. Clearly, although $y_{m,l}$ and $y_{m,l+1}$ are sampled with the same rate, they still play the role of details with different resolutions. The number of wavelet coefficients from expansions (16) and (17) are seemingly important in setting the resolution of each signal. On their turn, the coefficients are as many as the number of initial samples allows them to be (because of decimation).

In this context, the fused signal is expressed as a multi-resolution expansion as well:

$$x \equiv y_1 + y_2 + \cdots + y_L + x_L, \tag{18}$$

where y_l (for any $l \in \overline{1,L}$) and x_L are compounds selected from the sets $\{y_{m,l}\}_{m\in\overline{1,M}}$ and $\{x_{m,L}\}_{m\in\overline{1,M}}$, respectively. The sum of different resolution signals (18) can be effective only if all of them are sampled at the same rate (not necessarily the highest one). Thus, any detail of the fused signal, as well as the rough approximation, becomes from one of the M signals. Nevertheless, the resolution of the fused signal equals the resolution of the most refined signal from the collection, regardless the sampling rate.

Selection of constant resolution signals in (18) is performed by optimization of cost function $\mathbf{V}$. Whenever the number of distributed signals (M) and the coarsest resolution index (L) are small enough, the compounds of the fused signal can be found by exhaustive search over the sets of details and rough approximations. The number of combinations to test grows however exponentially (being equal to M^{L+1}). For this reason, if the two integers (M and L) are too large, the exhaustive search becomes ineffective. In this case, it is suitable to use a heuristic technique. One of the best adapted techniques to the framework above is the *Iterative Deepening Approach* (IDA*) from Artificial Intelligence [12].

The general goal of IDA* consists of finding the less expensive path within a tree. Costs of transition from a node to another must be assigned to the arcs of tree in this aim. The price paid when transitioning from root to a node following some path is then the sum of all costs assigned to its arcs. In order to reach for the goal as fast as possible, the general strategy of IDA* is based on the mechanism of tree pruning. Any branch of tree on which the estimated costs towards leaves are too high is completely removed (pruned) from the tree. Obviously, this operation can lead to a sub-optimal solution of problem, but the search duration can be reduced tremendously. The only requirement of IDA* is to operate with increasing path price depending on its length.

In case of wavelet based data fusion, the nodes of search tree are associated to *maps of details*. The map of tree root, $\mathbf{W}_0$, is illustrated in Fig. 5. On each column of $\mathbf{W}_0$, the details and the rough approximation of one distributed signal are enumerated in decreasing order of resolution. Null elements correspond to missing details.

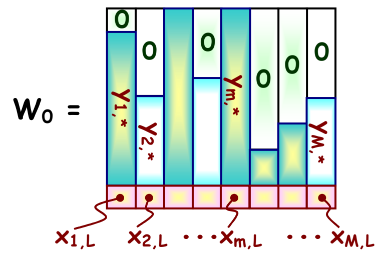

Fig. 5. Map of details associated to the root of IDA* search tree.

Obviously, $\mathbf{W}_0$ includes $L+1$ rows and M columns. Thus, the *fusion tree* has exactly $L+1$ levels of depth (beside the root) and each node can have up to M children, as shown in Fig. 6. Each depth level corresponds to a resolution index in representation of the fused signal.

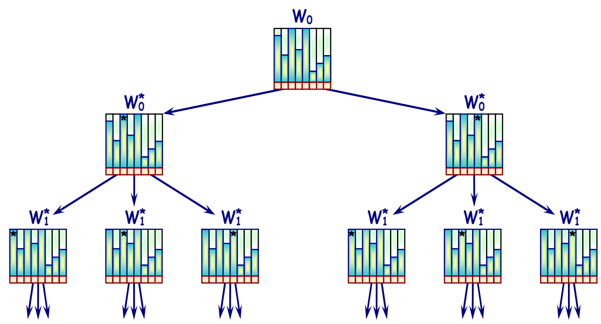

Fig. 6. A fusion tree based on wavelets

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The generic matrices assigned to the root children (on the first depth level) are identical to $\mathbf{W}_0$, but receive one star (*) on each non null elements of first row. Therefore, they are denoted by $\mathbf{W}_0^*$. The star points to the detail to consider when computing the partial expansion of fused signal, up to the current resolution. The next generic matrix, $\mathbf{W}_1$, becomes from $\mathbf{W}_0$, by removing the first row. There are $L+1$ generic matrices. Each matrix $\mathbf{W}_{l-1}$ produces the next matrix $\mathbf{W}_l$, by removing the first row. Finally, $\mathbf{W}_L$ reduces to one row that enumerates all rough approximations of distributed signals. Any matrix $\mathbf{W}_l^*$ assigned to a tree node is identical to $\mathbf{W}_l$, but includes one star on the first row. The star always points to the detail to consider in partial expansion of fused signal.
The cost of a transition from the current node to one of its children equals the value of $\mathbf{V}$, when considering the partial expansion of the fused

signal associated to the path from the root to that node. The price of a path is the sum of all transition costs. Also, the estimated price paid on the path from a node down to the deepest level of fusion tree is set as null (although some predictors can be employed as well).

The least expensive path found by IDA* includes $L+1$ nodes (beside the root). Let m_1, m_2, …, m_L et m_{L+1} the column indices of $\mathbf{W}_0$ selected in order by IDA* on the optimal path. Then the optimal fusion signal is:

$$x \equiv y_{m_1,1} + y_{m_2,2} + \cdots + y_{m_L,L} + x_{m_{L+1},L} . \quad (19)$$

During the search, partial expansions were compared in terms of costs. For example, in case of matrix from Fig. 5 (with 8 distributed signals), at the first step, one detail expansions $y_{3,1}$ and $y_{5,1}$ are compared. Thus, $m_1 \in \{3,5\}$. Next, the following expansions are compared:

$$y_{m_1,1} + y_{1,2}, \quad y_{m_1,1} + y_{3,2}, \quad y_{m_1,1} + y_{5,2}, \quad (20)$$

which involves that m_2 has to be 1, 3 or 5. Actually, m_2 corresponds to the minimum of the following 3 prices: $\mathbf{V}\left(y_{m_1,1}\right)+\mathbf{V}\left(y_{m_1,1}+y_{1,2}\right)$, $\mathbf{V}\left(y_{m_1,1}\right)+\mathbf{V}\left(y_{m_1,1}+y_{3,2}\right)$ & $\mathbf{V}\left(y_{m_1,1}\right)+\mathbf{V}\left(y_{m_1,1}+y_{5,2}\right)$. The value of m_2 points to the next node to expand, while the other nodes are kept on the fusion tree frontier. The expanded node is removed from the frontier and replaced by its children. Any of the nodes that lie on the tree frontier can be selected for expansion at some instant, provided that it is not on the deepest level. In this case, IDA* completes the search and returns the optimal path, which yields the optimal fused signal.

4. SIMULATION RESULTS

The data fusion algorithm based on wavelets has been implemented within MATLAB environment. Signals to be fused are vibrations acquired from a conveyor integrated in a robotic platform, as Fig.7 displays. A prototype of VISA and wireless communication between sensors (accelerometers) and the central unit have been employed in this aim. There are 6 sensors located along the conveyor (3 of each side, at different latitudes), nearby the bearings.

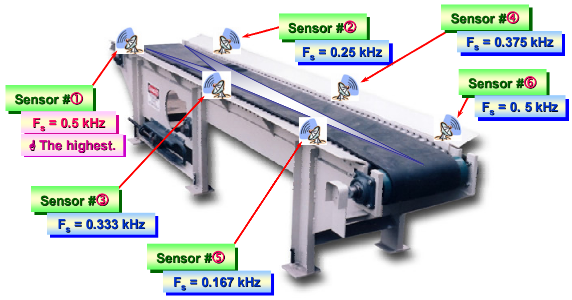

Fig. 7. Acquiring vibrations from a conveyor.

The conveyor is carrying some irregular metallic bodies, which are almost equally spaced. The robotic system is endowed with artificial vision and has to find and pick up the bodies from the conveyor. The sensors are working at different sampling rates, as shown in TABLE I.

TABLE 1: Sampling rates of 6 distributed sensors along a conveyor

Sensor #	1	2	3	4	5	6
Sampling rate [kHz]	0.5	0.25	0.333	0.375	0.167	0.5

The problem is then to compose a fused vibration in order to prevent either overcharging or jamming of conveyor. Such a vibration is significantly changing the frequency contents when any of the two behaviors are started.

The 6 acquired vibrations are illustrated in Fig. 8. Two fusion signals were derived: the mean one and the optimal one. After decomposing each vibration within the multi-resolution structure and re-sampling at the highest rate (0.5 kHz), the mean fused signal is just the average of the 6 re-sampled vibrations. The optimal fused signal resulted after running IDA*. Two light modifications occurred in the fusion algorithm. First, the entropy of wavelet coefficients ($\mathbf{W}$) has been added to the statistical parameters. Second, the square differences of criterion (5) were weighted according to their importance, as shown in TABLE II. Fig. 9 displays the mean (up) and the optimal (down) fusion vibrations. Although they look similar, the fitness is more than 16 times different in favor of the fused signal.

By definition, the *fitness* of a fused signal is the inverse of criterion (5). Thus, IDA* is actually maximizing the fitness of partial expansions. From 0.021796 (for the mean vibration), the fitness increased up to 0.367596 (for the optimal fused vibration), i.e. more than 16 times. This result was obtained for a couple of compactly supported orthogonal wavelets corresponding to $N = 3$ (Daubechies class), as illustrated in Fig. 9. Fitness varies with N like in TABLE III. Since vibrations are rather fractal, it is natural that high fitness values be obtained with fractal wavelets like the ones from Fig. 10. (Recall that wavelets regularity improves and the fractal dimension decreases, as N increases [7].)

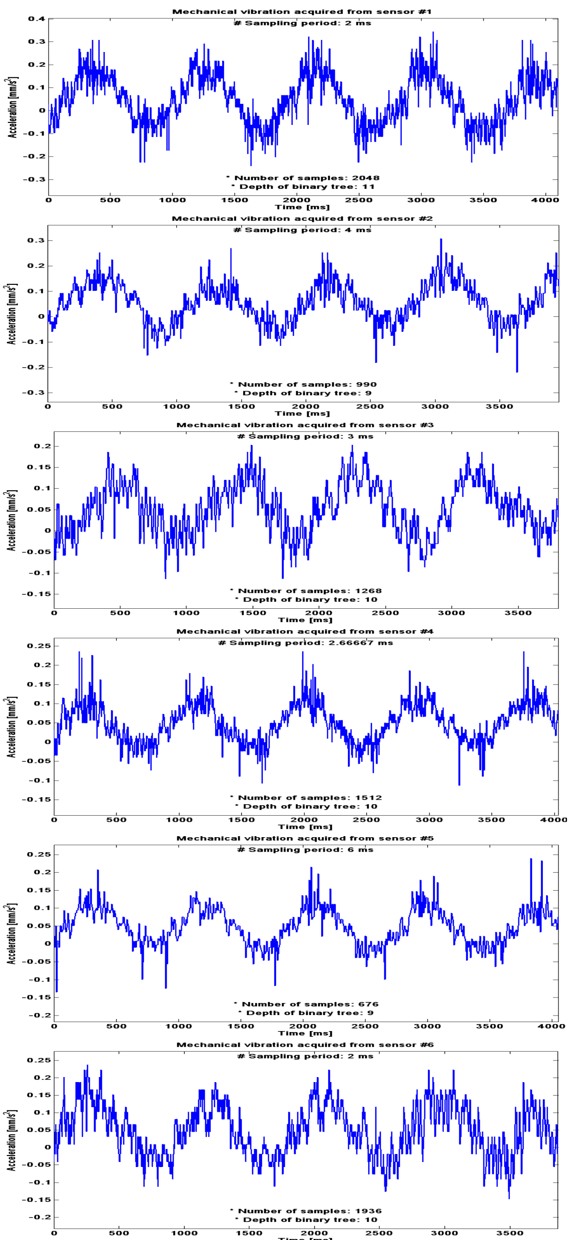

Fig. 8. Six distributed vibrations along a conveyor.

TABLE 2: Weights applied to statistical parameters

$\overline{x}$	**E**	RMS	Δx	CF	IF	SF	CLF	**K**	**H**	**W**
0.01	0.076	0.15	0.01	0.076	0.076	0.076	0.076	0.15	0.15	0.15

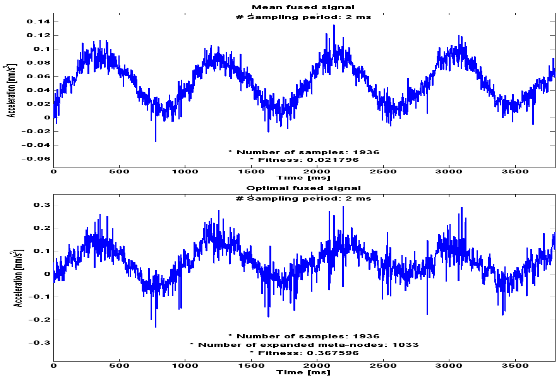

Fig. 9. Mean (up) and optimal (down) fused signals.

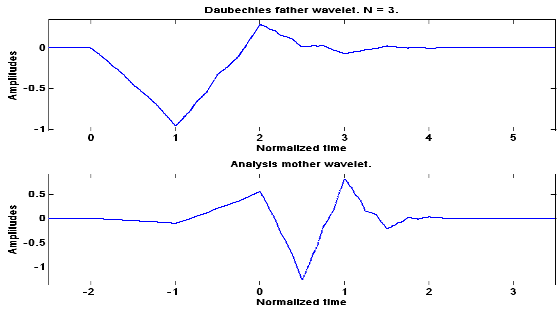

Fig. 10. Father (up) and mother (down) orthogonal wavelets for $N = 3$.

TABLE 3: Fitness variation depending on wavelets support parameter

N	2	**3**	4	5	6	7	8	9	10
1/**V**	0.317	**0.368**	0.334	0.345	0.326	0.312	0.192	0.17	0.155

The optimal path found by IDA* is: 1,1,1,1,1,1,1,1,5,4,5,6. In this case, vibrations from sensors 2 and 3 are only indirectly involved in construction of optimal fused signal. The two sensors could thus be misplaced.

5. CONCLUSION

Signal acquisition, primary processing, transmission, etc., are all parts of a mechatronic system. This communication introduced a signal acquisition solution (VISA) by using modern and versatile devices. The main goal of VISA is to provide distributed signals that can be aggregated by means of a data fusion technique. To the best of our knowledge, the fusion method succinctly described above is genuine. Usually, the fusion methods are applied to couples of signals and no optimization is performed. More specific, for more than 3 signals, first x_1 and x_2 are fused, then the result is aggregated with x_3, etc. By the method above, all signals are aggregated at once. Also, the former methods based on wavelets are simpler: one signal acts as the coarse approximation of fusion signal, while the details are all taken from the other signal. The method above can furthermore be generalized, by using wavelet packets [13].

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