Event-based signaling for reducing required data rates and processing power in a large-scale artificial robotic skin

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***Abstract*— In this paper we propose event-based signaling for large-scale artificial robotic skin to reduce bandwidth requirements on data transmission and processing power. We use the *send-on-delta* principle to trigger the event generation only when tactile sensors are stimulated and transduce novel information. To compare the standard non-event based method with the proposed event-based method we present a comprehensive analysis of large-scale artificial skin systems for different test applications. For this purpose we collect data of 260 CellulARSkin cells on an UR-5 arm and calculate the events off-line. We determine the optimal packet size for event-based signaling and we show that the event-based system reduces the data rate with respect to the non-event based system for an unstimulated skin cell network to 16.45% and for a heavily stimulated skin cell network to 47.69%. The obtained results show that the event-based system reduces the data redundancy and the required transmission rates without loosing information.**

I. INTRODUCTION

A. Motivation

Nowadays multiple solutions for modular artificial robotic skin like RoboSkin [15], [16] and CellulARSkin [11]–[14] exist. Main problems remaining with artificial skin in general are the required transmission rate to convey information of hundreds – in the near future even thousands of skin cells covering a whole robot – to higher processing layers and the required processing power to handle massive amounts of tactile data in real-time or near real-time.

Yousseffi et al. [17] propose a generic real-time data acquisition system and processing framework for artificial skin which they call Skinware. This synchronous framework triggers sensor readouts at constant rates and thus the framework decides when to acquire sensor data and when to compile tactile frames for higher processing layers.

To the best knowledge all artificial skin architectures so far comply to the standard method of sampling tactile sensor data at constant rates. The main reason is that many signal processing and control algorithms rely explicitly on constant sampling rates. However sampling tactile information at constant rates reaches its limits when large amounts of artificial skin cells cover large areas or even whole robot bodies since the required transmission rates and processing power increases.

Such setups reveal one disadvantage of sampling and processing information at constant rates: large amounts of information are transmitted and processed as sensing, transmitting

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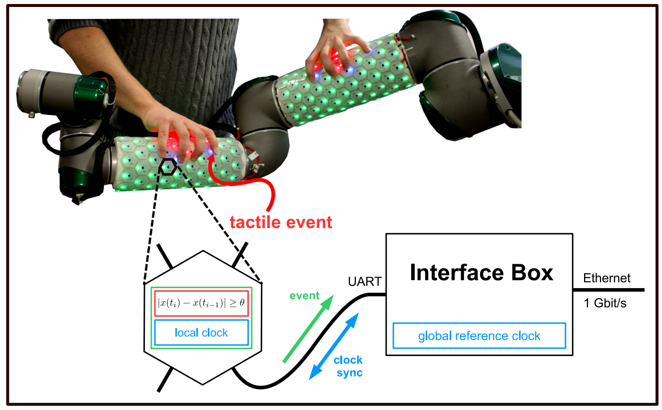

Fig. 1. For the evaluation of our proposed event-based skin network we use an UR5 robot arm which is equipped with 260 CellulARSkin cells; the image shows the skin cell network on the UR-5 arm as it is stimulated and as it generates tactile events; the different LED colors give feedback about the modality of tactile stimuli; resting skin cells are green, skin cells detecting pre-touch stimuli are red and skin cells detecting force stimuli are blue; the lower part of the image drafts our proposed event-based skin cell network.

and processing is not triggered by novel information but by constant time intervals enforced by the synchronous system. As solution we propose to change the trigger source and sense, transmit and process information only when new information is available, when some external stimuli are present and need to be processed. Considering that most of the time sensors sense constant values which don't contain novel information, as the values are already known at the higher processing layers, then such a concept would remove unnecessary information and relieve the transmission and processing system.

However we need to consider that redundancy takes an important role with respect to the robustness of a system. Nevertheless, we can use the same argument as in the discussion analog versus digital systems. One advantage digital systems have over analog systems is that digital systems purposefully reduce the amount of information of band limited signals and represent information in a consistent systematic and robust way. As a consequence one can easily add specific redundancy to the signals which exclusively improves robustness. For this reason digital signals allow small bandwidth signal transmissions, as not needed information is removed, while these transmission can still stay robust and reliable. With respect to event-based signaling it is a fact that we remove unnecessary information but as long as we only remove information which is not essential for robustness

the signal remains reliable. Moreover adding redundancy for improving robustness is usually possible.
Actually biological systems make massively use of novelty triggered signals, the so-called *events*. Sensory neurons produce actions potentials, whenever the experienced change of information exceeds a certain threshold. Besides reducing data rate and required processing power, novelty triggered information has a much higher temporal precision as sampled information. The new information is handled when new information is perceived by the sensor system and not when the synchronous sampling system enforces the sampling. We believe that event-based signaling for artificial skin poses a viable solution for handling tactile sensory information at a large scale.

B. Related Work

Multiple works exists on how to generate and transmit sensory events in artificial, technical systems. The work of Lichtsteiner et al. [1], Posch et al. [2], [3], Bartolozzi et al. [4], [5] and Benosman et al. [6] address event based retinomorphic dynamic vision sensors (DVS). They use the temporal contrast $\mathrm{TCON}(t)$ in combination with contrast thresholds to generate events at pixel level and use the address event representation (AER) to convey events from the pixels to higher layers. The image sensor has an outstanding low data rate, extremely high temporal resolution and a high dynamic range and enables efficient event-based processing at higher layers. Dahiya et al. [13] already pointed out that tactile events and feature extraction are important for data reduction purposes and Mittendorfer et al. [14] implemented tactile events using normalized tactile event levels at a higher abstraction layer to reduce data rate and enable grasping with the HRP2 robot.
The *send-on-delta* concept, introduced in [7] and [8] is a simple event based concept which uses difference thresholding for reducing transmission rates in wireless sensor networks. Recently [9], [10] developed extensions for the *send-on-delta* concept to further reduce transmission rate and reconstruction errors. We use the results of these works and introduce an enhanced and extended event-based concept for large-scale artificial skin.

C. Our approach

In this paper we propose a first concept on how to generate events in an existing CellulARSkin cell network without the need to redesign the existing hardware. We evaluate how the concept influences data rate and required processing power. Our concept bases on the *send-on-delta* concept since it can easily be adopted to our system. As CellulARSkin cells don't have any event generating sensors we decide to use a *compound architecture* [8] where sensor values are sampled as fast as possible but where the *send-on-delta* concept triggers the event generation and transmission. Our event packets will contain the skin cell ID, a timestamp and the absolute new sensor value. Before the actual implementation we focus on the quantitative evaluation of the proposed system to reduce data and transmission rate. For this purpose we perform prototypical applications using an industrial robot arm (UR-5) equipped with artificial skin (see Fig. 1). The arm is equipped with 260 CellulARSkin cells distributed in the most significant links of the robot namely the forearm, the upper-arm and the tooltip. During test applications we collect sensor data and calculate the events off-line. This allows us to compare the original data to the results of the event-based system. In the near future we will implement the event-generation directly in the skin cells. In this way we can evaluate the concept on-line and take advantage of the system in future applications.

II. SYSTEM DESCRIPTION

A. CellulARSkin and skin cell network

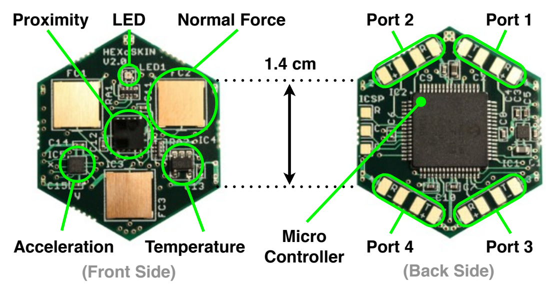

Fig. 2. CellulARSkin.

CellulARSkin [11]–[14] is a modularized artificial skin. Each hexagonally shaped skin cell is equipped with the same set of multi-modal sensors and one microcontroller. The microcontroller collects and filters sensor data and puts the gathered information as a packet into the skin cell network. The skin cell network (see Fig. 3) is self organized and highly redundant and the group of distributed microcontrollers manages the network. The distributed microcontrollers create packet routing paths and forward incoming packets to neighboring cells or to higher layers via the interface box.
Each skin cell samples 9 sensor values – 3 for the 3D accelerometer, 3 for the 3 force cells, 2 for the 2 temperature sensors and 1 for the proximity sensor – with a maximum rate of 250 Hz and injects packets to the network with the same rate. For performance reasons and for taking advantage of the microcontroller's DMAs the packet size cannot vary

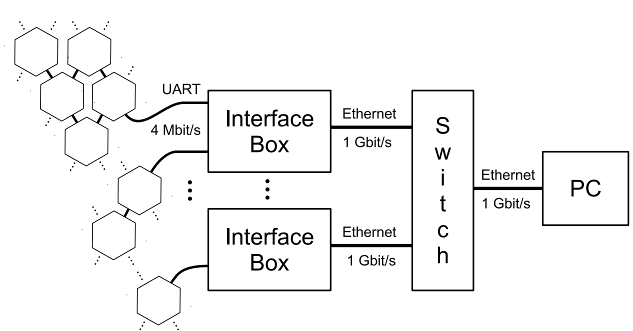

Fig. 3. The skin cell network architecture and interface to the PC.

and is fixed to 20 bytes. The inter-cell-connections are 4 Mbit/s fast UART connections and the skin cell network connects via interface boxes and standard 1 Gbit/s Ethernet connections to the PC. The interface boxes contain FPGAs which handle the communication between the UART based skin cell network and the Ethernet connection to the PC, see Fig. 3.

Each UART bus can support up to 66 skin cells and can handle 16000 packets/s. Overall a 1 Gbit/s Ethernet connection can support up to 5742 skin cells and can handle up to 1.49 Mio. packets/s.

The data load, the huge amount of small packages and the data organization are the limiting factors for the current architecture rather than insufficient transmission bandwidth. These are the main reasons why we propose event-based signaling in this work.

B. Event generation

1) The ideal event generating sensor: The ideal event based sensor needs not to be sampled at all, the sensor generates the events at its own, whenever it is stimulated with new information. The event generation is completely asynchronous and events can occur continuously at any time. Such an ideal event based sensor approximates infinite sampling rate and has a very high temporal precision.

Lichtsteiner et al. [1] and Posch et al. [2] developed an event based dynamic vision sensor which comes very close to the ideal event generating sensor. Each pixel of the image sensor creates independently an on or off event whenever the difference Δ_{x} between the light intensity of the last transmitted event and the currently measured light intensity exceeds a fixed threshold θ:

$$\Delta_{\mathrm{x}} = |\ln(x_i) - \ln(x_{i-1})| \geq \theta \quad \Rightarrow \mathrm{gen.\,event} \tag{1}$$

In this way the pixels as event generators are sensitive to the temporal contrast TCON

$$\mathrm{TCON}(t) = \frac{1}{x(t)}\frac{\mathrm{d}x(t)}{\mathrm{d}t} \approx \frac{1}{x_{i-1}}\frac{x_i - x_{i-1}}{\Delta t} \tag{2}$$

and generate events whenever the accumulated temporal contrast exceeds the threshold θ:

$$\left| \int_{t}^{t+\Delta t} \mathrm{TCON}(t)\,\mathrm{d}t \right| = \Delta_{\mathrm{x}} \tag{3}$$

Thus on/off event are generated whenever the change of intensity normalized to the last intensity exceeds the threshold θ. This makes the pixel very sensitive to small absolute intensities and less sensitive to bigger absolute intensities which explains the high dynamic range of the sensor. The on/off events are conveyed by an asynchronous bus which implements the so called *Address Event Representation* (AER). In the AER each event of a pixel is represented by a pixel address while the creation time of the event is encoded by the occurrence of the event on the bus. This yields in very high, nearly continuous timing precision. Whenever an event with AER on an asynchronous bus needs to be transfered into a synchronous system like a PC then the asynchronous to synchronous bridge has to add high precision time-stamps to the event.

Clearly the main advantage of this AER based implementation is the high temporal precision but – since the asynchronous bus must represent addresses – the implementation relies on fast and wide communication buses which are only available in VLSI CMOS circuits like FPGAs or ASICs. Transmitting only on/off events will also introduce offsets in the reconstruction of absolute values whenever an event is lost.

2) The send-on-delta concept: The *send-on-delta* concept for generating events proposed in [7], [8] is quite similar to the temporal contrast TCON principle introduced by [2]. The *send-on-delta* concept proposes to send only sensor values when the difference Δ_{x} between the last sent value $x(t_{i-1})$ and the currently measured value exceeds a static fixed threshold θ:

$$\Delta_{\mathrm{x}} = |x(t_i) - x(t_{i-1})| \geq \theta \quad \Rightarrow \mathrm{gen.\,event} \tag{4}$$

In contrast to the temporal contrast principle the sensor generates now events whenever the accumulated contrast

$$\mathrm{CON}(t) = \frac{\mathrm{d}}{\mathrm{d}t}\,x(t) \tag{5}$$

exceeds the threshold θ. So the sensitivity doesn't change with the sensor value and the difference which triggers an event is the same for all sensor values. The advantage is that the *send-on-delta* concept works for *compound architectures* [8]. In compound architectures sensor values are sampled as fast as possible but the transmission of sensor values follows the *send-on-delta* concept. Naturally this system has a lower temporal precision since the precision is limited by the sampling frequency of the conventional sensor. However events generated by the *send-on-delta* concept can use any arbitrary bus structure. Generally globally synchronized time-stamps should be locally added to the events at the event generation site. In this way the causality between events of distributed event generators can be reconstructed.

Sending absolute values as proposed by the *send-on-delta* concept has the advantage that the signal reconstruction from events at higher layers is offset free and doesn't suffer from event losses.

C. Event based signaling for artificial skin

We propose a simple event based signaling concept for artificial skins which allow its implementation in the current CellulARSkin version without the need to modify the hardware or the skin cell network architecture. We cannot use the almost ideal AER principle since we cannot realize asynchronous buses and the CellulARSkin cell doesn't contain any event generating sensors. For this reason, we aim for a system which makes use of the *send-on-delta* concept. In order to time-stamp events with the global time, the local time of the distributed microcontroller has to be synchronized to the global reference time which is provided by the FPGA of the interface box (see Fig. 1). One solution for this hard problem could be to use concepts of existing time synchronizing algorithms like the NTP (Network Time Protocol) or the more precise PTP (Precision Time Protocol) to the needs of our skin cell network architecture. However the exploration of this solution is out of the scope of this paper.

As the current skin cell network implementation relies on constant packet sizes we also need to determine the new optimal packet size for events. The idea is to make the packets big enough such that multiple events fit in to one packet. In this way whenever several events occur at the same time these events can be sent immediately with small overhead rather than separately with big overhead. Nevertheless event packets have to be small enough to keep the overhead small in case that only one single event needs to be transmitted.

III. Experiments

A. Difference thresholds and RMS reconstruction errors

In order to achieve efficient event generators we have to choose the fixed thresholds θ for each sensor value carefully. For this purpose we calculate differences between samples of the respective sensor values for all skin cells in the skin cell network. Then we analyze the distribution of differences (see Fig. 4). We ensure that all the skin cells are idle while we collect the data for this evaluation. Idle skin cells in this context mean that they remain at a constant pose in space and that they are not stimulated by tactile events. Finally we calculate for example the differences Δ_{a_x} for accelerations along the x-axis of the sensor as follows:

$$\Delta_{a_x} = a_x(t_i) - a_x(t_{i-1}) \tag{6}$$

The criteria to find the optimal value for the threshold θ is to find the best compromise. On the one hand the threshold needs to be high enough such that the event rate is low for idle sensors with noise and on the other hand the threshold has to be small enough such that the event generator is sensitive to small changes in order to reduce

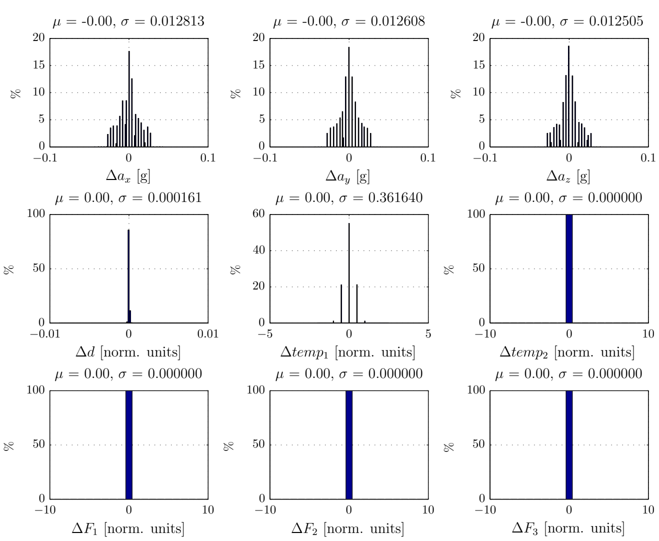

Fig. 4. Distribution of differences Δ of the 9 different sensor values for a skin cell network of 260 resting CellulARSkin cells; we observe that the accelerometer, the proximity sensor and the first temperature sensor of an idling skin cell have a wide distribution of differences while the distributions of the second temperature sensor and the 3 force sensors are quite narrow; from these results we deduce that the accelerometer and the proximity sensor contain more noise and therefore get larger thresholds.

TABLE I

Thresholds for the event generation

	a_x, a_y, a_z	force 1, force 2, force 3	prox.	temp. 1, temp. 2
θ	0.02	0.001	0.0001	0.5

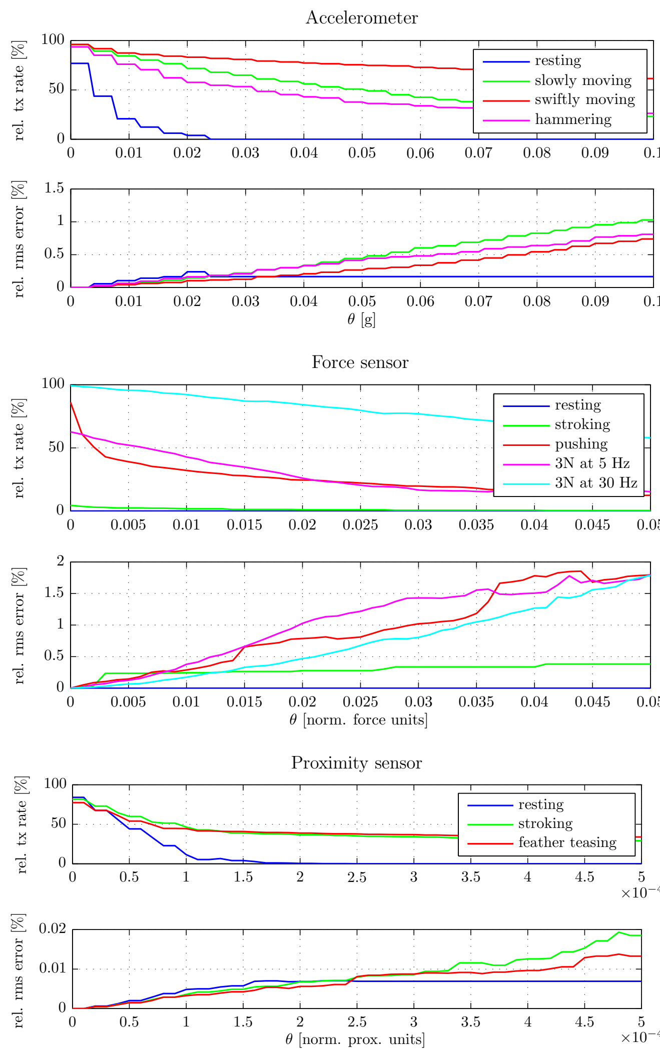

Fig. 5. Event rates and RMS reconstruction errors for different test applications; the figure shows measurements of different sensor modalities of one skin cell; in the *resting* test the sensors are unstimulated and idling and for an optimal threshold θ we expect a very low event rate for all sensor modalities; in the *slowly moving* and *swiftly moving* tests the UR-5 robot arm repeats a defined trajectory several times with different speeds and we expect higher event rates for the acceleration sensors; in the *hammering* test we generate impacts on the base of the UR-5 robot arm such that the skin senses vibrations and we expect higher event rates for the acceleration sensors; in the *stroking* test we expect higher event rates for force and proximity sensors; in the *pushing* test we forcefully move the UR-5 robot arm with the fist into different directions and thus we expect a high event rate on the force sensors; in the *feather teasing* test we tickle the UR-5 robot arm with a feather which induces high event rates on the proximity sensors; we also provide event rates for tests where we apply a force of 3 N to a skin cell at different frequencies by using a force test stand (see [11]).

the reconstruction error. In general, the threshold θ defines the boundary between what the event generator interprets as idling and what it interprets as small changes.
We see in Fig. 4 that the standard deviation σ is a good first indicator for choosing an appropriate threshold θ. For standard normal distributions we find that setting $\theta = \sigma$ is a good trade-off. In this way the event generator discards 68% of the samples while the remaining 32% of the samples correspond to noise like small vibrations induced by the resting robot arm. Nevertheless to find an optimal threshold for small event rates and small reconstructions errors for a wide range of applications we analyze how event rates and RMS errors for different sensor modalities and different test applications change with different thresholds θ (see Fig. 5). We decide to use the thresholds of Table I. For all these thresholds the RMS reconstruction error stays below 0.5%.

B. Applications and global event rates

We want to study how the event based signaling behaves with respect to the non-event based signaling. For each of the sensors we set the transmission rate in relation to those of the non-event based system. In other words we use the transmission rates of the non-event based system as reference. A skin cell network has n_{cells} skin cells which all sample sensor data and transmit the acquired data with a rate f_{s} . Thus in a non-event-based skin cell network all the n_{cells} cell are active at all times. The number of active cells $n_{\mathrm{cell,\,act}}$ at time t for the non-event based system is:

$$n_{\mathrm{cell,\,act,\,ref}} = n_{\mathrm{cells}} \cdot f_{\mathrm{s}} \cdot t \tag{7}$$

and the ratio of active cells of an event-based skin cell network with respect to the non-event based is:

$$p_{\mathrm{cell,\,act}} = \frac{n_{\mathrm{cell,\,act}}}{n_{\mathrm{cell,\,act,\,ref}}} = \frac{n_{\mathrm{cell,\,act}}}{n_{\mathrm{cells}} \cdot f_{\mathrm{s}} \cdot t} \tag{8}$$

The relative activity of the different sensor values in the global skin cell network scope can be calculated similarly in the following way:

$$n_{\mathrm{mod,\,act,\,ref}} = n_{\mathrm{cells}} \cdot f_{\mathrm{s}} \cdot t \tag{9}$$

$$p_{\mathrm{cell,\,act}} = \frac{n_{\mathrm{mod,\,act}}}{n_{\mathrm{cells}} \cdot f_{\mathrm{s}} \cdot t} \tag{10}$$

and we can find the results for our test applications in the upper part of the table in Fig. 6.

	resting	slowly moving	**swiftly moving**	hammering	stroking
a_{x}	9.90 %	46.6 %	68.3 %	49.3 %	13.1 %
a_{y}	9.27 %	43.2 %	65.2 %	48.2 %	13.0 %
a_{z}	9.29 %	45.9 %	68.2 %	48.6 %	12.0 %
prox.	6.51 %	6.98 %	7.54 %	9.73 %	14.6 %
temp. 1	3.17 %	3.37 %	4.57 %	3.74 %	2.45 %
temp. 2	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
force 1	0.00 %	0.00 %	0.00 %	0.00 %	0.517 %
force 2	0.00 %	0.00 %	0.00 %	0.00 %	0.518 %
force 3	0.00 %	0.00 %	0.00 %	0.00 %	0.403 %
active cells	**32.9 %**	80.0 %	**90.1 %**	77.2 %	43.9 %
1 sens. active	28.0 %	33.0 %	16.6 %	25.0 %	33.4 %
2 sens. active	4.52 %	29.5 %	28.7 %	25.4 %	8.64 %
3 sens. active	0.350 %	15.9 %	39.6 %	23.5 %	1.38 %
4 sens. active	0.0131 %	1.57 %	5.08 %	3.16 %	0.283 %
5 sens. active	0.00 %	0.0285 %	0.157 %	0.101 %	0.0865 %
6 sens. active	0.00 %	0.00 %	0.00 %	0.00 %	0.0286 %
7 sens. active	0.00 %	0.00 %	0.00 %	0.00 %	0.00159 %
8 sens. active	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
9 sens. active	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %

Fig. 6. Relative global transmission rate ratios for 260 skin cells for different test applications; the upper part of the table displays the global transmission rate ratios respectively for the different sensor values of all skin cells in the skin cell network; this transmission rate ratio is with respect to the non-event based sensor value rates and not with respect to the whole skin cell network transmission capacity; the active cell ratio describes how often skin cells in the network are active, and need to send a packet with at least one event, with respect to the non-event based skin cell network; the lower part of the table shows how many events occur at the same time and could be transmitted in a single packet.

C. Optimal packet size

The packet size is fixed within the skin cell network. If we continue to use the packet size of the current non-event-based skin cell network the average transmission rate ratio for the event-based implementation will be equal to the ratio of active cells $p_{\mathrm{cell,\,act}}$ that is for our test applications at most 90.1% (see Fig. 6). In the lower part of the table in Fig. 6 we observe that such an implementation is far from optimal since most of the time only 1 sensor is active – it is extremely unlikely that all the 9 sensors of a skin cell are active at the same time. For this reason we need to find the optimal packet size which minimizes the transmission overhead. First we define a set of packet sizes which fit for different numbers of events (see table II).

TABLE II
PACKET SIZES IN BYTES FOR DIFFERENT AMOUNTS OF EVENTS

$n_{\mathrm{e,\,pkt}}$	1	2	3	4	5	6	7	8	9
$s_{\mathrm{pkt}}(n_{\mathrm{e,\,pkt}})$	7	9	10	12	14	15	17	18	20
$s_{\mathrm{pkt,\,ts}}(n_{\mathrm{e,\,pkt}})$	10	12	13	15	17	18	20	21	22

$n_{\mathrm{e,\,pkt}}$ is the number of sensor events which fit into one packet and $s_{\mathrm{pkt}}(n_{\mathrm{e,\,pkt}})$ is the packet size in bytes for a given number of sensor events that fit into that packet. $s_{\mathrm{pkt}}(n_{\mathrm{e,\,pkt}})$ is chosen in such a way that any combination of $n_{\mathrm{e,\,pkt}}$ sensor events fits into that packet. $s_{\mathrm{pkt,\,ts}}(n_{\mathrm{e,\,pkt}})$ is the packet size when we add a 21 bit time-stamp to the packets. In the next step we determine how many packages will be transmitted when we use packets that fit for $n_{\mathrm{e,\,pkt}}$ events. Therefore we need to find out how often the skin cells need to transmit $i = 1, 2 \ldots 9$ events at the same time. We determine these numbers $n_{\mathrm{sens,\,act}}(i)$ for our different test applications. If the i events that need to be transmitted don't fit into one packet, then several packets need to be transmitted consecutively. The number of packets to transmit $n_{\mathrm{pkt}}(n_{\mathrm{e,\,pkt}})$ up to time t is then:

$$n_{\mathrm{pkt}}(n_{\mathrm{e,\,pkt}}) = \sum_{i=1}^{9} n_{\mathrm{sens,\,act}}(i) \cdot \left\lceil \frac{i}{n_{\mathrm{e,\,pkt}}} \right\rceil \tag{11}$$

Now we calculate the transmission rate ratios of the skin cell network $p_{\mathrm{pkt,\,data}}(n_{\mathrm{e,\,pkt}})$ with respect to different packet sizes and different test applications:

$$p_{\mathrm{pkt,\,data}}(n_{\mathrm{e,\,pkt}}) = \frac{n_{\mathrm{pkt}}(n_{\mathrm{e,\,pkt}})}{t \cdot f_s \cdot n_{\mathrm{cells}}} \cdot \frac{s(n_{\mathrm{e,\,pkt}})}{s_{\mathrm{ref}}} \tag{12}$$

$s_{\mathrm{ref}} = 20$ is the reference packet size of the non-event based system in bytes. The results are presented in Fig. 7. The

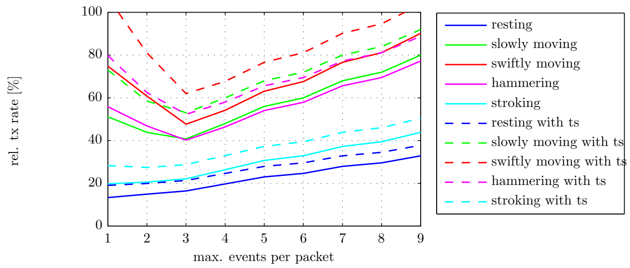

Fig. 7. Global transmission rate ratio versus number of events fitting into one packet; the solid lines refer to packets without time-stamps and the dashed lines refer to packets with time-stamps

	resting	slowly moving	**swiftly moving**	hammering	stroking
without time-stamps					
1 event/packet	13.35 %	51.13 %	74.84 %	55.86 %	19.80 %
2 events/packet	14.96 %	43.87 %	60.79 %	46.85 %	20.59 %
3 events/packet	**16.45 %**	40.78 %	**47.69 %**	40.24 %	22.13 %
4 events/packet	19.73 %	48.00 %	54.18 %	46.39 %	26.38 %
5 events/packet	23.02 %	55.98 %	63.09 %	54.05 %	30.89 %
6 events/packet	24.66 %	59.98 %	67.61 %	57.91 %	32.89 %
7 events/packet	27.95 %	67.98 %	76.62 %	65.63 %	37.28 %
8 events/packet	29.59 %	71.97 %	81.13 %	69.49 %	39.47 %
9 events/packet	32.88 %	79.97 %	90.14 %	77.21 %	43.86 %
with time-stamps					
1 event/packet	19.07 %	73.04 %	106.9 %	79.80 %	28.30 %
2 events/packet	19.95 %	58.49 %	81.05 %	62.47 %	27.45 %
3 events/packet	**21.38 %**	53.02 %	**62.00 %**	52.31 %	28.77 %
4 events/packet	24.66 %	60.00 %	67.72 %	57.98 %	32.98 %
5 events/packet	27.95 %	67.98 %	76.62 %	65.63 %	37.30 %
6 events/packet	29.59 %	71.97 %	81.13 %	69.49 %	39.47 %
7 events/packet	32.88 %	79.97 %	90.14 %	77.21 %	43.86 %
8 events/packet	34.52 %	83.97 %	94.65 %	81.07 %	46.05 %
9 events/packet	37.81 %	91.97 %	103.7 %	88.79 %	50.43 %

Fig. 8. Average global transmission rate ratios for different packet sizes with respect to the former non-event based system; the optimal packet size enables the transmission of 3 events at the same time; the event-based skin cell network uses then only 16.45% of the original transmission rate for the resting skin and only 47.69% for heavily stimulated skin when the UR-5 robot arm is moving swiftly; when time-stamps are added to the packets the resting skin uses 21.38% of the former transmission rate and the heavily stimulated skin 62%.

optimal packet size is the one which suits for 3 events. This is a reasonable result since the signals generated by the 3D accelerometers are highly correlated. The event based system overall shows a very good data reduction behavior. Even for the heavily actuated UR-5 robot arm the event based network only uses 47.69% of the original system's transmission rate, or respectively 62.0% when adding time-stamps to the packets. For a resting skin cell network the transmission rate ratio is only 16.45%, or respectively 21.38% for packets with time-stamps. See figure 8.

IV. CONCLUSIONS

The paper introduces and evaluates quantitatively and qualitatively an event-based system for large-scale artificial skin networks and analyzes the system's potential to greatly reduce required data transmission bandwidths and processing power. For performance evaluation we collected data from 260 CellulARSkin cells attached to an UR-5 robot arm for a wide range of different test applications. The wide range of different test applications allows us to estimate bounds for the data reduction rates of the event based system in real-world applications. The quantitative analysis shows that the event-based system is able to reduce the transmission rate to 32.9% for resting, unstimulated skin and 90.1% for heavily stimulated skin. If we choose the optimal constant packet size for events then the reduction rates improve to 16.45% or 47.69% respectively. Still the reconstruction error remains low such that information loss is minimal. Future improvements could embrace signal dependent or in general non-constant thresholds which might improve reconstruction errors and sensitivity.

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