Adaptivity to Enable an Efficient and Robust Human Intranet

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ABSTRACT

The Human Intranet is envisioned as an open, scalable platform that seamlessly integrates an ever-increasing number of sensor, actuation, computation, storage, communication, and energy nodes located on, in, or around the human body, acting in symbiosis with the functions provided by the body itself. The limited amount of available energy and the critical nature of its applications require such a network to be extremely efficient and robust. This paper introduces a learning-based adaptive network structure to overcome these challenges. The adaptive structure is implemented and tested in two sample scenarios and the results are reported.

INTRODUCTION

Wireless technology has evolved rapidly in the past decades—in particular there has been an increased development of more wearable, implantable, and personal devices. These are now mainly standalone devices that interface either directly or via a personal device with the network and the user. However, an evolution towards an interconnected network of those devices on the human body is expected [1], similar to what has been seen for the increased number of interconnects between off-body objects in the world. The Human Intranet (HI) [2] is envisioned to serve as a platform for this network. However, some aspects are particularly challenging in the development of the HI. The nodes in the network are expected to be diverse in terms of function, information rate, intelligence, form-factor and energy availability. Moreover, the communication mechanisms between the nodes are also diverse [3, 4]. Depending on the required range, location (e.g. implanted or not), data rate, security and energy availability, different communication technologies might be appropriate. The addition and removal of nodes to adjust functionality should happen in an intuitive and scalable way. Finally, since the critical functions of the human body might depend on this network, it needs to be designed in a reliable, robust, and secure manner.

An open question is what kind of strategy should be followed in the design and operation of such an on-body network. Different solutions exist at all layers of the wireless network stack, from the physical and data link layers up to the application layer. The extreme energy and latency constraints require global solutions that operate close to the optimal. Yet, it is extremely unlikely that a single solution can be found that is optimal over all use cases [5]. In addition, the network is highly dynamic, and optimal configurations might change from one moment to another. Addressing this requires the use of multi-layer feedback, where changes in one network layer
might influence choices in the others. Therefore, in this paper, we propose to use an adaptive, learning-based multi-layer HI network model.

In the next sections, the potential modalities, characteristics, and dynamics in the different layers of the network are discussed with a focus on the lower layers of the wireless network. This will motivate the need for a reliable, adaptive, multi-layer network. This architecture has to be generic enough to cover all different scenarios, but also allow addressing the simple cases without much overhead. A strategy for modeling this multi-layer stack is presented, and a framework for the design and operation of such an adaptive, heterogeneous network is described. The potential gains of the proposed approach are illustrated in two real use cases.

**HI ADAPTIVE HIERARCHY**

The HI architecture is an adaptive communication architecture for wireless body area networks (WBANs). Figure 1 illustrates the proposed architecture consisting of two orthogonal planes: a network data plane and an adaptive control plane. The data plane follows a standard wireless sensor network stack (from bottom physical layer to the top application layer). The adaptive control plane manages the dynamic evolution of the network. The following sections describe the two orthogonal planes, their layers and components, and how they can be intersected to create adaptive services.

![Figure 1](image-url)

*Figure 1. a) The Human Intranet with its different components; b) the two planes of the adaptive communication architecture: the adaptive control plane consisting of the knowledge (KNO), learning (LEA), and decision (DEC) components, and the network data plane consisting of the physical (PHY), medium access control (MAC), network (NET), and application (APP) layers; c) adaptive architecture formed by intersecting the network data plane and adaptive control plane in different moments of time with services and connectors.*
NETWORK DATA PLANE

Among the many existing network protocols and topologies, the unique characteristics and requirements of HI makes only a handful of them suitable for this type of network. This chapter gives a brief overview of available choices in each network layer, i.e. physical (PHY), medium access control (MAC), network (NET), and application (APP) layer, along with a comparison of their specifications and limitations.

While there have been great efforts such as IEEE 802.15.6 to standardize parts of the protocol stack, we do not limit our available options to those standards and instead try to pick the protocols from the general classes in each layer. Moreover, no single “best” protocol or topology satisfies all daily life scenarios [6]. Thus, a more optimal solution can be achieved by adapting the protocol based on the human activities and environmental changes.

Physical Layer

There are four scenarios for physical layer wireless body channels: (1) On-body: from one part on the surface of the human body to another; (2) in-body: from inside the human body, typically to the body surface; (3) off-body: from the surface of the human body to the network; (4) body-to-body: from one subject’s body to another subject’s body. This paper focuses on the on-body network, but the other channels are part of the HI as well. Wireless on-body communication predominantly happens through two different physical mechanisms: electromagnetic fields (EMFs) and mechanical waves. Mechanical wave propagation, including ultrasound, sonar, bone vibrations and other similar mechanisms, is often used in configurations where EMF attenuation would be severe. However, the limitation in operating frequency for these mechanisms also limits the achievable bandwidth. Moreover, EMFs allow for a natural compatibility with existing wireless telecommunication networks. Therefore, on-body EMF-based networks are studied and used more frequently.

The main difference between on-body wireless communication and regular telecommunication is the constant presence of the body, which dynamically absorbs, scatters, and blocks the waves used for communication, and causes efficiency losses in the devices used to register and generate those fields, i.e. antennas, transducers, diodes, coils and electrodes. Additionally, the presence of the body implies a lower limit in output power than what is allowed in free space. This results in reduced ranges and data rates in comparison with free-space communication. Table A shows a non-exhaustive overview of the different types of EMF communication that are commonly used in on-body communication.
Table A: Overview of different types of Electromagnetic (EM) on-body wireless communication. The different techniques are classified into Far-Field, Near-Field, and Body-Coupled Communication.

|                          | Far-Field                          | Near Field                        | Body-Coupled Communication |
|--------------------------|------------------------------------|-----------------------------------|-----------------------------|
|                          | Active RF [4]                       | Passive RF [7]                    | mm-wave [8]                  |
|                          | Inductive, capacitive, and resonant | Inductive, capacitive, and resonant |
|                          | Coupling [10]                      | Coupling [10]                     | Capacitive, galvanic, and inductive [3] |
| Frequency (GHz)          | 0.013-11                           | 0.01-1                            | 57 – 95                      |
|                          |                                   |                                   | 15-75×10³                   |
|                          | 0.001-0.4                          |                                   | 0.0001-0.6                   |
| Achievable On-Body Data | 100                                | 0.600                             | 100                          |
| rate (Mbps)              |                                     | < 1000a                           | 7000                         |
|                          |                                     | 4                                 | 400                          |
| Maximum On-Body Data    | 1000                               | 0.640                             | 1000                         |
| rate (Mbps)              |                                     | 7000                              | 400                          |
|                          |                                     | 4                                 | < 80                         |
| Range (m)                | Full Bodyb                         | Half Bodyb                        | Full body (indoor), O(10³)   |
|                          |                                     |                                   | (outdoor)                    |
|                          | <2                                 |                                    | 0.005-0.03                   |
|                          |                                     |                                   | 0.05-2                       |
| Bandwidth (MHz)          | 1 - 7000                           | < 0.5                             | Up to O(10⁶)                 |
|                          |                                     |                                   | < 10                         |
|                          |                                     |                                   | < 40                         |

a Determined for around body communication (transmitter and receiver are off body)
b ‘Full Body’ coverage refers to the potential to cover any location on the body from any location on the body, while ‘Half body’ refers to the potential to cover only the half of the body that does not require around body propagation.

Far-field EM communication is widely used due to its compatibility with the existing wireless networks. Far-field techniques operate in different frequency ranges: RF (radio frequency) [4], mm-waves [8], and optical [9], with increasing (potential) bandwidth and smaller device sizes at higher carrier frequencies. However, the increased on-body path loss reduces the range in comparison to the lower RF frequencies. In general, higher frequencies (higher RF, mm-waves, and optical) experience high path loss during so-called around body communication. In particular, on-body optical wireless networking relies on scattering from an indoor environment to achieve coverage [9].

Any of the listed communication types could be operated in a passive or active mode. We have chosen to explicitly divide far-field EM communication into active and passive communication, in order to illustrate the difference between both approaches. Generally, passive communication results in reduced performance due to a reduction in sensitivity on the passive end [7]. However, it allows operation without a power source on one end of the communication channel.
Near-field EM communication overcomes the issue of on-body path-loss altogether by only communicating over a very short range [10]. Usually, this technique is a passive-type of communication, which can be capacitive, inductive or resonant magnetic. The frequencies used are lower in order to stay in the near (or mid) field of the devices during communication on the body. Consequently, the bandwidths and data rates are lower than those achieved in the far-field solutions.

Body-Coupled or Intra-Body Communication uses the human body as the channel for communication among on-body nodes [3]. Due to the high propagation loss in the human body for EMFs, the range of such solutions is limited. However, security comes almost by design for these applications due to restricted communication range, and there is high compatibility with communication towards implants.

In the physical channel, the transmitted power between different nodes is quantified using (channel) path loss. This is a dynamic parameter whose variance is quantified by the channel fading, which is caused both by factors external to the body and movements of the body. Instantaneous path losses can become very significant and typical path losses for many on-body radio links are still very large [4]. This makes communication on the human body challenging. However, the channel can be stable for hundreds of milliseconds.

In order to demonstrate this stability, we have executed signal strength measurements using an on-body RF EMF link at 2.4 GHz (nRF51822, Nordic Semiconductor) [15] from wrist to hip during four activities, as illustrated in Fig. 2a to 2c. As Fig. 2d shows, a large fading (variation on signal strength) can occur, even for presumably rather passive activities. However, this does not necessarily imply that the channel is not stable or predictable. The temporal autocorrelation [11] of different channels is often used to quantify stability using the channel coherence time, i.e. the period over which this correlation remains relatively high. Alternatively, it is possible to quantify stability using the channel variation factor [12], which is a running average of the ratio of the standard deviation to the square root of the mean power during a period. In this case, the period over which a channel remains stable is defined as the period during which this quantity remains low. As Fig. 2f shows, the autocorrelation factor remains relatively high over several 100ms, except for walking. However, the channel variation factor remains relatively low for this activity as well. This relative stability of the on-body channels enables accurate channel prediction across multiple communications frames, which can help to configure the transmit power and efficiently allocate the resources.

The measurements shown in Fig. 2 cover brief periods of time within the total operation time of the HI. On a larger time-scale, the predictability is potentially higher in the PHY layer due to recurrence of certain activities (sleeping time, transportation, etc.), environments (home, office, etc.), and applications in a subject’s daily life. The PHY characteristics of these different scenarios can be measured, learned, and adapted by the adaptive control plane, and used for the selection of the appropriate PHY channels and parameters of the wireless devices.
Figure 2. Received signal strength (RSS) measurements of the channel impulse response of the left hip to right wrist channel: a) the nodes [15] used to measure the channel signal strength over time; b) the four different activities that were considered in this experiment: standing upright, sitting at a desk, walking indoors, and laying down in sleeping position on the back, simultaneously; c) the approximate locations of the two nodes used in the experiment; d) the measured RSS during 16s with a sample interval of 1ms for the four studied activities. The grey lines show the actual measured signal strength values, while the black curves show a running average over 100ms. These data are used to obtain the estimates of variation shown in Fig. 2e on the bottom right; e) the temporal autocorrelation for the four activities as a function of the delay time (left), and the cumulative distribution functions for the channel variation factor as a function for an averaging time of 100ms for the same four activities.

MAC Layer

The main responsibilities of the Media Access Control (MAC) layer are to enable services for associating/disassociating nodes with the network and providing access control to the shared channel.

In WBANs, MAC protocols have a great impact on energy efficiency, reliability of communication, interference, the QoS (quality of service) provision, and prolonging network lifetimes by controlling packet collisions, overhearing, control overheads, and idle listening. They are generally grouped either as contention-based or scheduled-based or a combination of both (hybrid) protocols.
In contention-based protocols, such as Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA), the nodes contend for the channel to transmit data. If the channel is busy, they defer the transmission until it becomes idle. CSMA/CA protocols use low bandwidth, experience less packet failure, and provide good network scalability. Contention protocols can also adapt parameters such as back-off periods, wake-up interval, retransmissions policy, or listening time slots.

In schedule-based protocols, such as Time Division Multiple Access (TDMA), the channel is divided into fixed or variable length time slots that are assigned to each node. They transmit during their dedicated slot period. TDMA improves the power consumption in comparison to contention-based protocols but has latency problems with packet failures [13]. TDMA protocols are based on superframes with time slots for different proposes. The superframe may be structured in an active and an inactive part; during the latter, nodes can go into stand-by state to reduce their power consumption. The beacon listen period, active and inactive parts, number and length of time slots can be allocated dynamically, based on the network knowledge and predictions (traffic priority, human movements, activities, spectrum state, etc.).

Hybrid protocols, where there are dedicated time slots and contention access periods, can adapt all the previous parameters. Furthermore, they can use different channels or dynamically allocate contention periods with respect to those assigned. Based on its knowledge, the network could predict the communication link quality, traffic demand (depending on the type of sensors), and QoS (throughput, latency, reliability, security), and choose a suitable strategy in the MAC layer design to obtain the best performance. TDMA, CDMA, and hybrid protocols can all be adapted to different human body conditions.

**Network Layer**

The network (NET) layer provides the internetworking capability to the nodes. The main considerations of this layer are addressing, mapping and routing protocols. Traditional transport, session, and presentation layer functions, if necessary, are also included in this level.

Early WBANs [1] targeted pure data collection from a set of sensors at a central (a.k.a. sink) node. Therefore, a simple point-to-point star topology was sufficient for their application, and no routing or network layer was needed. However, later works [14] show that multi-hop links are unavoidable for various reasons. The unique lossy channel characteristics of the human body, as discussed earlier, make it impossible to directly link some nodes with a reasonable transmit power level. Also, the star connection does not work with implanted sensors which have very limited reach. Moreover, breaking a long link into multiple hops and consequently lowering the radio transmit power decreases power dissipation while reducing interference. The multi-hop scheme becomes even more appealing in the context of the HI, where the application is no longer limited to centralized sensor data collection and involves talking between any pair of nodes.

The design and development of efficient routing protocols for WBANs is a challenging job due to their unique requirements and specific characteristics. There are several routing protocols with diverse parameters that can be tuned based on different criteria and accounting for multiple factors to obtain the best performance for each specific application or situation. The routing protocols are divided into three groups, based on how the routing decision is being made: Centralized, where a
central node (hub) relays the incoming packets to their destination; *distributed*, where the routing decisions are made at more than one node; and *flooding*, where there is no decision to be made and all nodes rebroadcast what they receive.

Efficient routing protocol development requires a proper network topology as it affects the overall performance of the communication system. Proper network topology is very important for these networks because of the energy constraint, body postural movements, heterogeneous nature of the sensors and short transmission range. The network topology often faces the problem of disconnection or partitioning because of body postural movements and short-range transmissions. This problem could be solved using none-line-of-sight (NLOS) communication or store-and-forward routing.

Typical routing criteria are link stability, end to end cumulative cost, residual energy (local energy consumption of nodes and the overall network lifetime), and minimum number of hops. Regardless of the selected criteria, the protocols are affected by factors such as network topology, various QoS in the nodes, transmission range of nodes, security level, human posture (path loss), etc. All these factors have to be taken into account when carrying out an adaptive protocol. Each protocol is also application dependent, i.e., the protocols used for daily monitoring and the critical medical cases are different.

**Application Layer**

The role of the application (APP) layer is to abstract the physical topology of the WBAN for the applications. Moreover, the application layer provides necessary interfaces to the user to interact with the physical world through the network. The applications condition the rest of the levels of the network plane.

Some example groups that benefit from the HI are disabled people regaining body functions using smart prosthetics, patients relying on wearable medical devices, and athletes striving to be the best in their field. Each of these applications requires its own topology and specification in the APP layer.

**ADAPTIVE CONTROL PLANE**

Considering the predictive nature of the data plane, an adaptive control plane strategy can be adopted to provide optimal network operation. The adaptive control plane is composed of three interacting components: knowledge, learning, and decisions.

**Knowledge Component**

The knowledge (KNO) component manages all aspects related to the current knowledge that the system has. Knowledge management is a result of processes including synthesis, filtration, comparison, and analysis of available information. This component includes acquisition and storage, discovery and sharing, and representation of the knowledge.

This knowledge may be incorporated prior to the deployment of the system using data obtained from the outside world or generated through learning. It can be a database that contains all kinds
of description information for different application scenarios (environment monitoring, health care monitoring, etc.). It can also contain information about network routing, node positioning, data fusion, time synchronization, security control, topology control, condition monitoring, information collection, storage management, coverage control, data forwarding, and statistics reports. Other important information is sensing information where nodes store all kinds of historical data such as temperature, EEG (electroencephalogram), EMG (electromyogram), vibration, speed and acceleration for each node at different time period. In the final stage, the information is provided to the other components using knowledge representation techniques.

**Learning Component**

The learning (LEA) component hosts all the strategies and algorithms that allow increasing or modifying existing knowledge. This layer is essential to allow the adaptation of the system to new scenarios and situations. Learning algorithms can be categorized into: (1) Supervised learning: these set of algorithms use training data to generate a function that relates the inputs to desired outputs. For example, in a classification problem, the system looks at example data and uses it to arrive at a function mapping input data into classes. Artificial neural networks, decision trees, and radial basis function networks are forms of supervised learning. (2) Unsupervised learning: these set of algorithms work without previously labeled data. The main purpose of these algorithms is to find the common patterns in previously unseen data. Clustering, Hidden Markov models and self-organizing maps are the most popular forms of unsupervised learning. (3) Semi-supervised learning: as the name indicates, these algorithms combine labeled and unlabeled data to generate an appropriate mapping function or classifier. The most popular learning mechanisms in the field of prediction in WBANs are artificial neural networks (supervised).

One of the most important predictions in wireless networks applies to the wireless link status. These algorithms predict the time at which the signal quality will degrade, often from the handover perspective due to the interference. In WBANs, however, the signal quality degradation is mostly a transient condition caused by environmental or human body factors and does not eventually lead to a handover. As such, using historical data to predict disconnect duration would be instrumental in a lot of applications like health monitoring.

Efficient implementation of the learning techniques in real-time devices is essential. Some learning algorithms may provide more accurate predictions but are more computationally intensive. It is possible that these algorithms cannot be employed in any of the nodes because of the resource constraints involved. It is imperative to build efficient implementations of learning techniques for WBANs, which take into account the limited memory, computing power, and battery life in these networks.

**Decision Component**

Decision-making is defined as the process resulting in the selection (based on the values, preferences and beliefs) of a course or action among several alternative possibilities. Every decision-making process produces a final choice, which may or may not prompt action. The decision (DEC) component is responsible for making decisions on all aspects of the network. These decisions are based on knowledge and learning but also on inference and optimization. Decision-making techniques can be separated into two broad categories: group decision-making
techniques (consensus, voting-based methods, or Delphi method) and individual decision-making techniques (balance, rules, or optimizing/satisfying methods). The technique must be chosen according to the specific objective.

Modification of the configuration parameters, changing the MAC strategy, or adding a row to the routing table are examples of functions that are carried out at this level. Observing the effect of the made decisions is crucial for learning and providing feedback to the knowledge level.

The working flow starts by acquiring the knowledge, then processing that knowledge to make rational decisions and choose the best actions, and finally generating new knowledge based on those decisions. The decision-making algorithms are also a function of the available resources at each network node. Transversal functionalities such as security or power consumption are integrated at all levels, since they have to be part of the network design in a holistic way.

By intersecting the network and adaptive planes, a set of cells are created in which the services can be hosted (Fig. 1b and 1c). In this way, the architecture is composed of services, which belong to a certain level of the adaptive control and data network planes. Examples of services can be a database about the radio spectrum in a specific scenario (PHY-KNO), two different medium access implementations (MAC-DEC), or a neural network to learn the most efficient routing paths (NET-LEA). There are also services that could provide resources to the network, but they are hosted outside the network. Services are connected through connectors that provide and request service resources. There is no limit on the number of connectors per service, and the connectors can be used in every cell. Services can be composed of other services with connectors to provide a more general service.

Both services and connectors change over the network lifetime and can be created or disappear depending on the scenario. Therefore, for each moment of time the network has a configuration (services and connectors) that can be completely different, adapting its behavior to the specific moment.

Services can be implemented in both hardware and software, allowing the coexistence of all kinds of technologies and strategies. The use of connectors, a standard interface, enables a more accelerated development of network functionalities by facilitating the integration of services developed by different developers.

**SAMPLE APPLICATIONS**

The goal of this section is to demonstrate that the proposed adaptive architecture can be used to solve some of the key issues that arise in body area networks. We have selected two applications to demonstrate this. In a first example we demonstrate that the adaptive architecture is leveraged to save power while communicating during predictive movements. In a second application, we show that our proposed architecture enables more robust wireless control of prosthetics in critical applications.
Saving Power in Predictive Movements

The human body is limited in the potential movements that can be made. Consequently, the received signals in on-body communication are bound by these limits as well. The adaptive control plane introduces the possibility to learn from the received signals and potentially other sensors in the HI to predict the time-variations in the PHY layer and make appropriate adaptations in order to increase efficiency on multiple levels.

Figure 3 shows an example in which this functionality is demonstrated. The figure shows the received signal strength (RSS) over time in an on-body link at 2.4 GHz from wrist to opposite waist during walking (see Fig. 2a to 2c for the configuration). The adaptive control plane learns the frequency of movement, for example by executing a Fourier expansion, and adapts the transmitted power to anticipate the changes in path loss or choose the time of emissions in such a way that those only occur on moments when the path loss is relatively low. One basic option is to only transmit when the channel is good (high RSS), since it does not make sense to waste a lot of power when the channel is bad (low RSS). This strategy is shown in Fig. 3a. Additionally, the receiver can be brought into a sleep mode during the transmitter’s (Tx’s) off-time, and the on/off periodicity and relative time frames could be adapted to save even more power. Figure 3a shows measurements of the Tx node's power consumption as a function of the emitted power and indicates that the overall power consumption will go down when using an adaptive Tx power.

![Figure 3](image)

**Figure 3.** a) RSS power on the right hip (blue) emitted from a transmitter (Tx) worn on the left wrist with a constant emitted power, shown in Fig. 2b and 2c. During the KNO and LEA phases of the adaptive control first the frequency of movement can be determined using a 1st order Fourier expansion (black). This periodicity in the movement can then be used to adapt the Tx power (red), thus influencing the RSS; b) illustration of the active layers and components in the network and control plane, and their services and connectors in this example.
Robust Control of Prosthetics

Robust wireless control of prosthetic limbs is a challenging task due to the tight reliability and latency constraints. This section discusses another example of our adaptive network scheme, i.e. controlling a prosthetic arm based on the EMG signals gathered from the user's arm. Fig. 4a shows the network setup consisting of an EMG sensor array [15] on the right forearm, a processing unit (PU e.g. cellphone) in the pants’ opposite (left) pocket, and a prosthetic actuator hand on the same side as the sensor array. This would be a realistic scenario for an amputee who wants to control a bionic arm with their own muscle signals: 64 channels of raw EMG signals are recorded from the forearm and sent to the PU, hand gestures are classified at the PU based on the recorded EMG, and appropriate commands are sent from the PU to the prosthesis to perform the gesture.

The link quality between the PU and the end nodes (sensor/actuator) varies depending on the shadowing effect from different body postures and activities. For instance, line-of-sight (LOS) link exists when standing up but it is blocked when carrying an object with the arms. This leads to an unstable link for the critical application of controlling a prosthetic arm. However, our proposed adaptive structure can mitigate this issue.

Figure 4b shows the services and connectors used in this scenario. EMG signals (Fig. 4c) are recorded and streamed to the PU as a knowledge (APP-KNO). Using this data, a machine learning algorithm classifies the body state (Fig. 4d) as "standing" without the object (labeled as 1), "carrying" the object (labeled as 2), or "lifting" the object (labeled as 3) at the PU (APP-LEA). Our prior knowledge and learning of the physical layer (PHY-KNO and PHY-LEA) suggests that by staying at –4dBm Tx power level normally and going up to +4dBm when carrying or lifting an object, the link degradation can be compensated for. Therefore, the radio Tx power is adaptively toggled between these levels (PHY-DEC) based on the body activity (Fig. 4e). This makes the critical PU-prosthetic link more robust while saving power by not transmitting unnecessarily at the maximum level all the time. Figure 4f shows the RSS at the receiver. The received signal degradation after blockage is resolved after adaptively increasing the Tx power. After returning to LOS, the RSS jumps up for a while and the Tx power is lowered immediately after the classifier determines the new posture to save energy. Note that it is also possible to control the prosthetic arm’s intermediate movements based on the measured RSS, i.e. learn (LEA) from the PHY in order to tune the execution (DEC) in the APP.
Figure 4. Robust control of a prosthetic arm based on the EMG signals from the forearm: a) Node positions and body postures during "standing" without the object (labeled as 1), "carrying" the object (labeled as 2), and "lifting" the object (labeled as 3). Two wireless links, one from the EMG sensor array to the processing unit (PU) and another from the PU to the prosthetic arm are marked with red arrows; b) illustration of the active layers and components in the network and control plane, and their services and connectors in this example; c) 10 seconds of raw EMG voltages from 64 electrodes placed on the right forearm; d) the classifier output labels; e) the PU-prosthetic instantaneous Tx power level adaptively changing based on the classifier output; f) the RSS at the prosthetic.

CONCLUSION

The Human Intranet, i.e. a platform for wireless nodes in, on, and around the human body, faces several challenges in terms of scalability, power consumption, robustness, and security. The current network architecture used for body area networks is not suitable to deal with these dynamic, yet partially predictable properties. Therefore, an adaptive architecture is proposed that learns and reconfigures the network based on the prior knowledge as well as inputs from the environment and network itself. The different layers of this architecture are outlined and their dynamic nature is shown. Two sample applications targeting wireless power consumption and robustness are brought forward in which the proposed architecture improves functionality. The ultimate success of this
approach, however, depends upon the availability of energy-efficient learning-based processors, a domain that is receiving a lot of attention today.

ACKNOWLEDGMENT

The authors would like to thank Andy Zhou, George Alexandrov and Prof. Elad Alon. This work was supported in part by Semiconductor Research Corporation (SRC) under the STARnet SONICS and TerraSwarm centers and the JUMP CONIX center. Support was also received from sponsors of Berkeley Wireless Research Center. A.T. has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 665501 with the Research Foundation Flanders (FWO). A.T. is an FWO [PEGASUS]² Marie Sklodowska-Curie Fellow.

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