From Smart Clothing to Smart Table Cloth: Design and Implementation of a Large Scale, Textile Pressure Matrix Sensor

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Abstract. We describe the design and implementation of an unobtrusive, cheap, large scale, pressure sensor matrix that can be used for a variety of applications ranging from smart clothing, through smart furniture, to an intelligent table cloth or carpet. The specific functionality and with it most of the complexity lies in the electronics and the processing software. We propose a scalable, modular architecture for such electronics, describe a prototype implementation, and present the results of its application to three different scenarios.

Keywords: large scale data acquisition system, pressure sensor matrix, wearable and ubiquitous computing.

1 Introduction

Human activity recognition with ubiquitous sensors is a well established research area [1]. While, over time, a variety of sensor modalities have been proposed and evaluated, there are still many applications that are limited by the quality and reliability of information sources. In particular, the trade-off between the effort involved in the instrumentation of the environment and the amount of information provided by the system remains a key issue.

In this paper, we describe our research on unobtrusive, high density, high sample rate textile pressure sensor matrices. As described in Section 2, the actual sensor matrix can be produced cheaply by printing arrays of conductive lines on an elastic, high resistance material. The resulting device is essentially a piece of textile that can be used for a broad range of applications: from smart clothing through smart furniture to an intelligent table cloth or carpet (see Figures 5,6,7). The specific functionality and, with it, most of the complexity lies in the electronics and the processing software (following the concept of "textile-based wearable sensing as an app" [2]). Thus, given envisioned sensor densities of several points per cm^2 and sensor area of up to several m^2, a core problem is how to realize the required read-out electronics with appropriate sensitivity and refresh rates.

Related Work and Paper Contributions. Different pressure sensor matrices with flexible and thin features have already been proposed and demonstrated.

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Table 1. Overview on Existing Digital Pressure Matrix

application	modality	node amount	analogue precision	refresh rate
chair user posture [4]	resistive matrix	42x84	8-bit	6Hz
bed sleeper vital signs and posture[5] [6]	resistive matrix	16x16	unspecified	12Hz
shoes gait analysis [7]	opto-electronic	64 nodes	14-bit	1.8kHz
cushion user posture [8]	resistive matrix	16x16	unspecified	10Hz
commercial surface pressure mapping [9]	resistive matrix	32-by-32	discharging capacitor[a]	1kHz
driver comfort [10]	capacitive matrix	10x10	10-bit	100Hz
humanoid robotics	resistive EIT[b]	16[c]	unspecified	24Hz

[a] Discharging a capacitor is a low-end alternative to using an ADC. [11]
[b] Electrical Impedance Tomography, a technique to reversely estimate the resistance distribution of a conductive material only from the rim. [12]
[c] This number is only the physical electrodes; the calculated pressure mapping has higher resolution but is not specified by the authors.

A brief overview is given in Table 1, from which, it is easy to see, that current approaches are limited by the sampling electronics to raise the resolutions, conversion bits and refresh rates comprehensively. In [3], Bränzel, etc. recognize people and objects by sensing the pressure distribution in a room based on optical interference, where transparent glass floor with a large space underneath the testing room is required by the camera, using the camera to solve the hardware limits. Clearly such a solution involves much more installation effort than carpet-like textiles. Compared to the existing systems summarized above, the contribution of our work lies in a general hardware architecture topology which is:

- *large-scale.* The modularized hardware's complexity grows with n while the matrix's channel number grows with n^2. (detailed in Section 3) With existing hardware, the maximum channel number can be more than 10^6;
- *high pixel (analogue) and temporal (scanning rate) resolution.* Recent studies have shown high precision pressure sensor helps reveal subtle activities(e.g. four pressure force sensors under chair's leg can distinguish not only user's postures but also activities like nodding or moving the mouse. [13]). We thus choose 24-bit analogue-digital converters (ADCs) rather than low-end 10-bit integrated ADCs, the structural separation between the digital and analogue modules can minimize noise level;
- *suitable for a broad range of applications.* As demonstrated in Section 4, our system provides relevant information in applications ranging from on-body sensing through a smart table cloth to carpet-like structures.

In the paper, we first describe the basic sensing principle (Section 2). We then outline a generalized, scalable, adaptive architecture for the driver electronics (Section 3). This includes concepts for dynamic reconfiguration and data

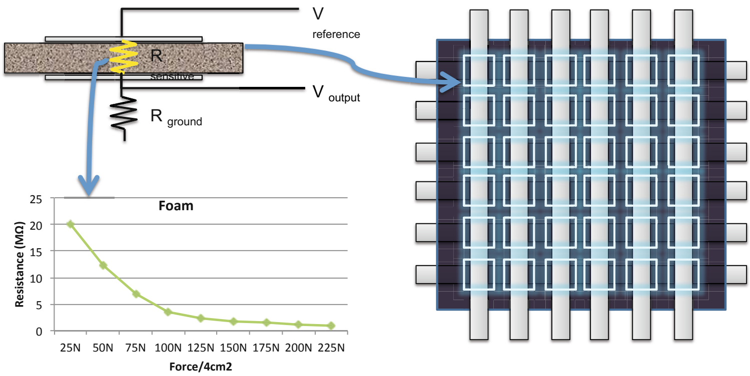

Fig. 1. Sensing Principle

compression schemes to reduce the data transmission load and facilitate real-time processing. It also encompasses a detailed analysis of the scalability in terms of size and sampling rate on the basis of existing off-the-shelf components. In Section 5 we then describe our first prototype implementation of the system and discuss performance results in three different scenarios (smart carpet for exercise monitoring, smart table cloth and wearable posture monitoring).

2 Textile Pressure Sensor Matrix

The general principle of our textile pressure sensor matrix is shown in Figure 1. The basis is a large area of a material that has high resistivity that can be locally reduced by applying vertical pressure. The force/resistance curve for the foam material used in the tablecloth example in Section 5 is shown in the bottom left part of Figure 1. Other materials can have steeper or gentler slopes and different regions of operation. For large body area wearable applications, material flexibility and 'feel' is also an important consideration.

Once an appropriate material has been selected, an array of conductive lines is attached to (or printed on) the upper and the lower side in such a way that the lines on the lower side are perpendicular to the lines on the upper side (as shown on the right side of Figure 1). Thus, at every intersection of two lines, a sensing element, as shown in the top left part of Figure 1, is generated. Each sensing element can be read out by measuring the resistance between the respective horizontal and vertical line.

3 Processing Architecture

3.1 Design Requirements

The concept of a large scale pressure sensor matrix as information source for activity recognition is motivated by the insight that many activities are determined by physical contact and changes in shape. Thus, for example, physical exercises (eg. push-ups, sit ups etc) involve different contact patterns between the body and the ground. Having a meal can be described by the placement and changes of weight of objects caused by food being moved from one plate to another and eaten, pressure being applied when cutting something on the plate, and the position of hands and arms. Body motion and posture can be acquired from changes in the pressure distribution between the body and tightly fitting clothes (e.g. as muscle expand on contraction).

From the above considerations, the following requirements can be identified for the processing electronics required for large scale sensing matrices suitable for activity recognition:

- *Spacial resolution.* Appropriate pixel density is essential for recognizing shapes of objects (feet, furniture legs, etc.) placed on relevant surfaces (floor, tables). In general a resolution in sub-cm range is desirable. Higher density clearly will offer more details; however, it also significantly increases data amount, so that a good tradeoff must be found.
- *Measurement sensitivity and dynamic range.* Studies such as [14] and [13] show that subtle difference in weight and weight distribution contain important information about user activities. In general a sensitivity well below 100g with a measurement range of well over a typical body weight ($\simeq$100kg) is required.
- *Sample rate.* Since not only identifying objects, but also recognizing activities is of interest, sufficient scanning rate must be appropriate for typical human motions, which is described as around 10Hz to 50Hz, according to relative studies.[15]
- *Scalability.* A key advantage of the proposed sensor system is the fact that the same basic textile structure can be used in a wide variety of applications. Obviously the core matrix structure scales well and different sized matrices can be easily combined to form large, complex systems. However this implies that the control and evaluation must also scale with respect to scanning rate, driving load and supported data rates. Thus, system sizes up to a mega-pixel (1024x1024) are conceivable in many applications.

3.2 Architecture

Based on the specifications discussed above, to achieve a large scale, high analogue precision, large channel amount system, we propose an architecture described in Figure 2. In this chapter the system design considerations will be discussed in details.

First of all, the sensor matrix is in fact constructed by intersecting two sets of parallel wires (X and Y). The sensor node between each conjunction can be abstracted as a block with an enable input, pinned to the corresponding Y wire, and an analogue output, connected to the X direction. During the scanning procedure, one Y wire is powered each time, enabling the nodes with the same Y to generate outputs on the X wires. A complete frame is done by sweeping the

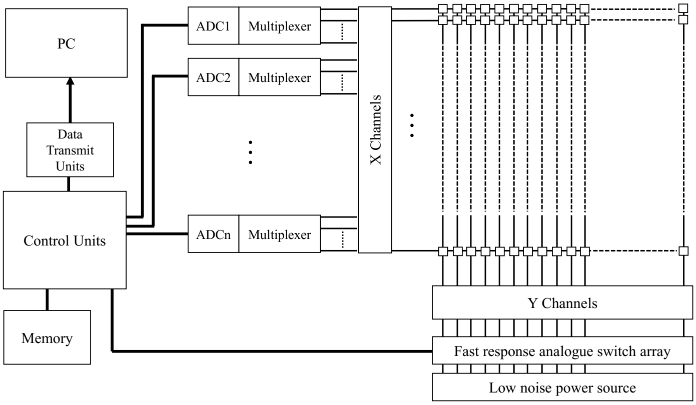

Fig. 2. Matrix Data Acquisition System Architecture

Y axes to address all the sensor nodes. As an example to illustrate the amount of data that needs to be processed, we consider a 128-by-128 system.

High analogue precision always requires low noise level. To achieve this we separate the digital and analogue parts and equip the analogue part with ultra low noise power supply ICs. The Y electrodes are separated from the digital part by fast analogue switches. The addressing sequence can be implemented by several layers of demultiplexers; however, in our architecture, a single IC with sufficient I/O pins is chosen to simplify the printed circuit board (PCB) and facilitate complex control and scanning strategies.

The X electrodes need to be connected to ADC input channels for sampling; we choose single channel high precision ADCs for the flexibility in building the structure. In general it is impractical to have a dedicated ADC channel for each X line. Therefore, we put analogue multiplexers in front of the ADC to route analogue signals. To route 128 channels into one ADC input using existing devices requires at least one base layer of four 32-to-1 multiplexers and a second level layer of 4-to-1 multiplexers, which in turn increases noise and settling time. The settling time increase applies to every sample and thus has a big influence on the scanning rate. Our approach uses a hybrid combination of ADC-multiplexer blocks to balance performance and cost: each block includes one ADC and a 32-to-1 multiplexer as the front end, and four of these blocks can cover 128 channels.

A master control unit coordinates the scanning sequence, reads out the ADC sampling result, processes data and sends the data to the computer. The control units including the master unit and the demultiplexer unit are FPGAs, with a high number of I/Os and the capability to process the data from multiple ADC-multiplexer blocks simultaneously. The data transmission method is flexible. Available options include: a serial port, Universal Serial Bus, Gigabit-Ethernet, Peripheral Component Interconnect Bus, etc. The choice should be made based on the actual data bandwidth and the complexity of developing the local drivers on the computer.

3.3 Performance Limits

In the following part, a calculation is carried out to see how much spatial resolution our architecture can achieve based on the analogue components commercially available today. Since on the X direction, several ADC-multiplexer blocks operate simultaneously, in principle, the analogue sampling timing does not limit the resolution. However in practice we must consider the fact that the product of X and Y channels determines the overall data rate in each frame and, with it, the required processing power of the control and data transmission unit (in the case that on-board data compression is not implemented). Assuming the ADC-multiplexer blocks have 32-to-1 multiplexers, each block controls $32 \times Y$ nodes. Figure 3 shows the timing components of a single ADC-multiplexer block within a frame. Since the blocks operate in parallel, the timing components of a single block determine the timing of the entire frame. Looking at the performance of currently available off the shelf components we have the following:

- high performance ADCs (24 bit, $2.5MHz$ output sample rate, $100dB$ Signal-to-Noise ratio) with a $2500ns$ complete sample-conversion cycle (T_{ADC});
- high speed analogue switch with $T_{Yon} = T_{Yoff} = 10ns$ at the Y channels;
- high speed 32-to-1 analogue multiplexers with $T_{Xon} = T_{Xoff} = 30ns$ on and off times at the X channels.

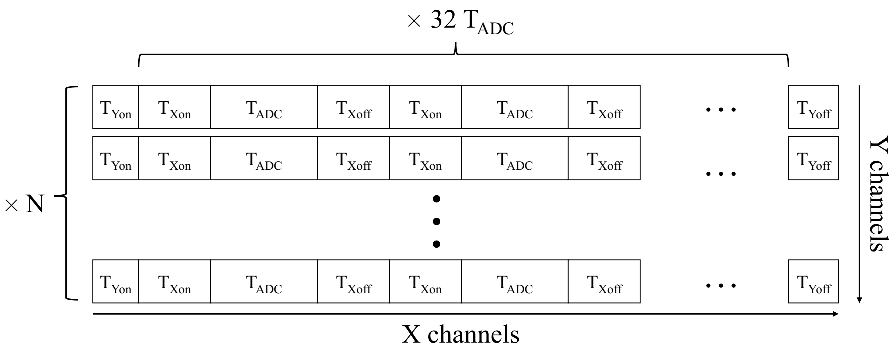

Fig. 3. ADC-Multiplexer block timing components

Thus, to maintain a maintain a 50Hz scanning rate the following constraint should hold:

$$[m \times 2560ns + 20ns] \times N \times R < 1s,$$

$m = 32$, multiplexer input channels;
$R = 50$, scanning rate;
N: Y channels.

The maximum integer value of N meeting this constraint is 244. With 8 blocks, a 255-by-244 matrix can be configured. From the above constraint, the Y channel limit N increases with less analogue multiplexer input channels m. Therefore

Table 2. Scalability – small to large scale designs with the same architecture

	Small (Prototype)	**Medium**	**Large**	**Tessellation**
Scale	32×32	128×128	1024×1024	$16 \times 255 \times 244$
Multiplexer	32-to-1	32-to-1	8-to-1	32-to-1
ADC-MUX blocks	1	4	125	128
Refresh rate	>50Hz	50Hz	47Hz	50Hz
ADC precision	16-bit	24-bit	24-bit	24-bit
demultiplexer controllers I/Os	32	128	1024	16×244
Data rate (uncompressed)	100kB/s	2.4MB/s	141GB/s	16x9.1MB/s

more ADCs are needed to achieve higher spacial resolutions. This structure can fully utilize the ADC sampling time.

3.4 Scalability

From the constraint in section 3.3, having $m = 8$ and $N = 1024$ will result in $R < 47.6$. That is to say, using 8-to-1 analogue multiplexers and having 1024 Y channels, the system will still have a scanning rate of 47Hz. With 125 ADC-multiplexer blocks, the system can scale up to 1024-by-1024, i.e. mega-pixel level. Another alternative for scaling is to tesselate a big matrix with several intermediate-sized systems as submodules, in which case, there is the option to process the data either centrally, distributedly or in a hybrid fashion. Tessellation with distributed data processing in theory can unlock the scale limit, because it is essentially a duplication of the base system. Table 2 summarizes the above mentioned scalability of the architecture.

3.5 Dynamic Reconfiguration and Data Compression Schemes

As described above, our architecture scales well with respect to the timing limits of the analogue components. However, from Table 2 it can be seen that data rates generated by the system will become a bottleneck as the scale of the system goes up. Even though PCIe interfaces can now deliver speeds up to 128 Gbps (Gen3) [16], there is still consideration of power consumption, system size and etc. Luckily, there is significant potential to reduce the data rate. The uncompressed data from matrix shares great similarity with gray-colored video ($1024 \times 1024@50Hz$ vs. $1280 \times 720@25Hz$) in:

- *temporal redundancy.* Most of the human activities are of low frequencies ($< 20Hz$), so there is similarity from frame to frame.
- *spatial redundancy.* There is similarity between adjacent channels. And more importantly, for pressure matrix is the ratio of triggered to un-triggered

channels. Taking a carpet covering a $3 \times 3m^2$ living room with 3 people for example, when the people are standing or walking around, maximum 6 feet ($30 \times 10cm^2$) are triggering the carpet, which, for 1024×1024 resolution, means 200 channels, uncompressed data-rate 30kB/s. The information about furniture, which are stable, can be sent as a base-frame from time to time.
– *statistical redundancy.* The distribution of 24-bit codes are not the same. For everyday activity recognition, subtle activities which result in small signals (e.g. move head/hand, walk around, cooking) are much more likely to happen than activities with big pressure distribution change (run, drag big furniture, roll about on the floor).

With FPGA included already in the architecture, first-step compressions such as applying a threshold to remove the un-triggered channels can be done for each ADC in parallel. This may bring even further advantage: reducing power consumption. Because the process of scanning each channel is controlled by FPGA, combined with parameters feed back to FPGA from on-line processing software, the scanning rate for un-triggered channels can be dropped to a much lower value. (E.g. a program detecting human feet and only the area of possible next step is scanned at a high speed.)

We would like to mention that our paper puts emphasize on the hardware architecture. For that we explain here only the potential of data compression. How to modify and implement existing compression methods for image and video to the pressure matrix lies in our future work.

4 Implementation and Results

4.1 Prototype Hardware

To test the architecture and demonstrate the capability of the sensor matrix we made out of low cost materials, a prototype of 32-by-32 channels with 16-bit ADC precision was built. The prototype's hardware structure is shown in Figure 4. It is not exactly the same as the architecture described in Section 3, but the overall structure falls into the architecture. The ADC with 32-to-1 multiplexer is integrated in a micro-controller; since the ADC precision does not require ultra low noise power on the Y channels, the FPGA I/O pins are connected directly to the Y channels.

The sensor matrix is made by attaching two perpendicular arrays of electrode stripes (aluminium foil on fiber-glass reinforced polypropylene tape) on two sides of flexible resistive material sheets, of which the volume resistance changes with the deformation caused by pressure. We use two different materials to represent carpet and cloth separately. The spacial distance on X and Y directions between pixels is $30mm$ for the former and $20mm$ for the latter.

4.2 Results and Application Examples

We have used the prototype to acquire and analyse signals in three scenarios that were already mentioned in the paper: (1) physical exercise, (2) a 'smart

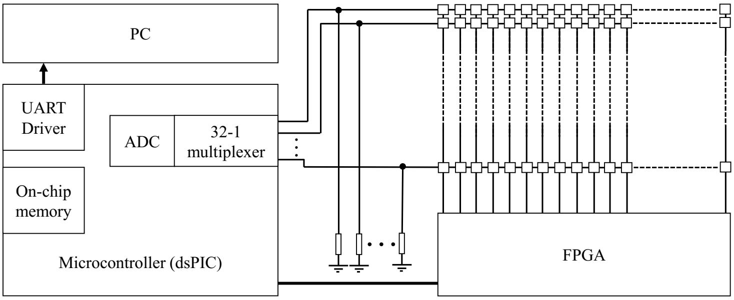

Fig. 4. Prototype System Structure

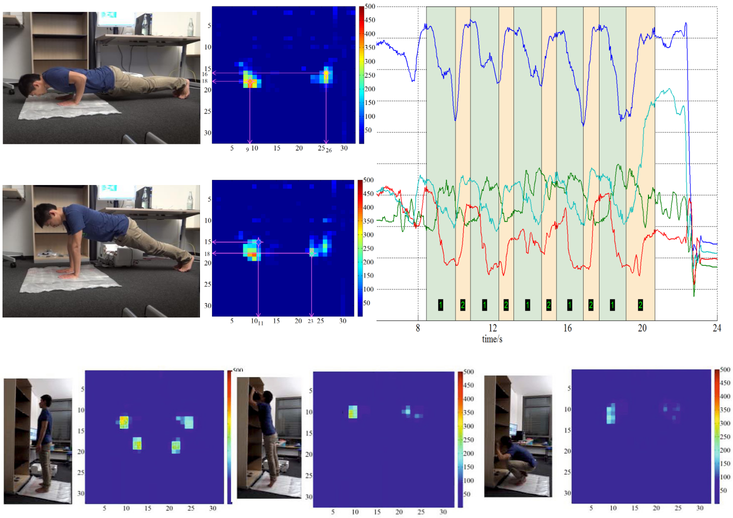

Fig. 5. Prototype Experiment Result: push-ups on the top, reaching shelves on the bottom)

tablecloth' and (3) sensing body shape changes with tight fitting garments. These scenarios represent a broad rang of applications with different requirements with respect to resolution and fore sensitivity. Since the focus of this paper is on sensing system design, not on activity recognition, we refrain from doing actual recognition (which is subject of future work). Instead, we focus on demonstrating that our system can acquire signals that reflect the differences between relevant situations and actions.

Detecting Physical Exercise with a Mat. We consider a person exercising on the floor. Specifically Figure 5 shows the signals acquired when doing push-ups with hands on the smart mat made of our sensor matrix. It can be seen that the force distribution between hands and the sensor matrix is different when moving downwards and upwards. On a downwards move the forces are more evenly distributed across the hand, because the arms are trying to support the body against gravity and achieve a fluent speed. When moving upwards, the forces are more focused near the waist joint since the arms are actively outperforming against gravity to push the body upwards. In addition, the distribution between the left and the right hands shows asymmetry caused by more weight being placed on the dominant hand. The movement process is more obvious in the dynamic data of several marked nodes in Figure 5. It can be seen that the signal contains a clear pattern for every push up instance that could be easily used to for counting.

On the bottom of Figure 5 the same system is used to detect a person reaching diferent locations of a shelf. It can be seen that, when standing still, the signals show the pressure from the toes to the heel. When stretching up the pressure is focused on the toes, in the low position the pressure is spread out on the soles of the feet. Note that the overall pattern is distinctly different from the push ups.

Smart Table Cloth. Next we consider our pressure matrix being placed on a table as a 'smart tablecloth' to detect different types of objects (plates, glasses, bottles etc) and the weight changes associated with their content being consumed. As an example, Figure 6 shows the signal produced by an empty and half full bottle of mineral water. The observation can be made. First, in both cases the shape of the bottle bottom can be clearly seen. Second there is a clear difference in the signals between the empty and the half full bottle. Similar results were achieved with plates, bowls etc. Hands and arms placed on the table also show distinct signals.

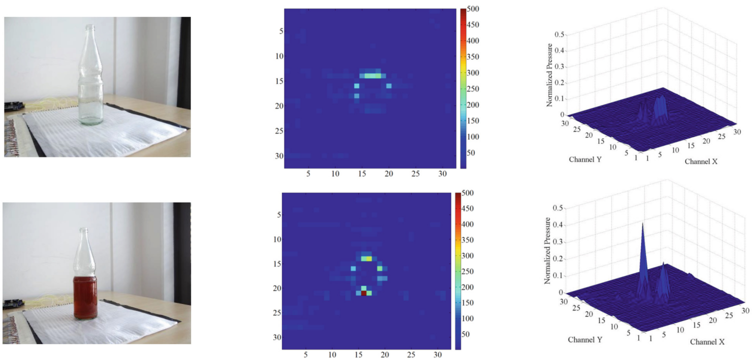

Fig. 6. Prototype Experiment Result: table cloth

Wearable Sensing. To investigate the suitability of the proposed system for on-body sensing, the matrix previously used for table cloth has been first wrapped around the users upper and lower arm. The resulting signal is shown in Figure 7 a) and b). It can be clearly seen that the signals differ significantly for a straight and flexed elbow.

Second ,we have placed the matrix in the trousers on the buttock to compare the signals for different sitting situations. Figure 7 shows the signals obtained from sitting on a chair and leaning on the edge of a table. Again a clear difference can be seen.

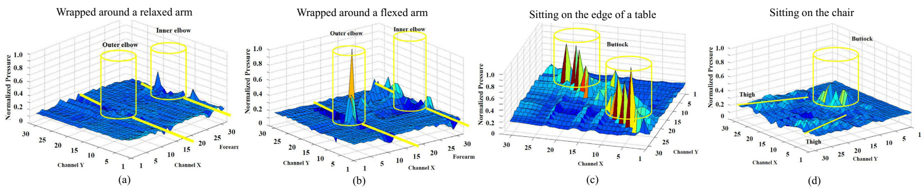

Fig. 7. Prototype Experiment Result: wearable scenarios

5 Conclusion

The main conclusion from the work presented in this paper is that large scale textile pressure matrix that produce information relevant to a variety of context recognition tasks is feasible. In particular we have shown that, using existing commercial components, system sizes of up to 1024x1024 (1 million individual sensors) are feasible with sample rates of up to 50Hz.

As a next step, we are currently working on demonstrating the actual recognition of different activities (e.g. distinguishing different exercises and counting repetitions). In parallel a larger version of the system will be deployed on the floor of the social area of our lab in a long term experiment.

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