

Hard Sensors for Soft Phenomena

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About this talk

The goal is to give an introduction to sensors and the difficulties to measure phenomena related to human activity from the perspective of a researcher working with multiple physical devices, such as robot teams.



Overview

1. Concepts about sensors
2. Finding patterns
3. Designing sensors
4. Final remarks



Concepts



Concepts (1)

transducer: device that converts variations of a signal in one form of energy into another form of energy.

In Robotics and Electronics, a transducer is commonly a device that converts a physical non-electrical signal into an electrical signal, i.e., a microphone converts “sound”, air pressure, into an electrical signal.

Signals converted from transducers can be recorded, amplified, processed, and so on.

sensor: a transducer that converts a physical stimuli into electrical signal that a microprocessor can read.

Concepts (2)

Strictly speaking, a sensor is a kind of transducer. However both terms are commonly interchanged.

Sensors enable a machine, e.g. a robot, a smartphone, to perceive both its internal state and its surrounding.



Concepts (3)

Most sensors fall into two categories according to their output:

Digital sensors return discrete values, e.g. contact with an object.

Analog sensors return continuous values, e.g. lightning intensity.

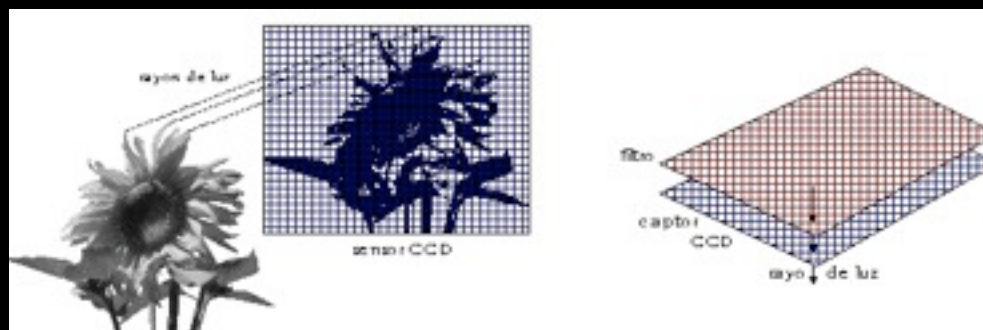
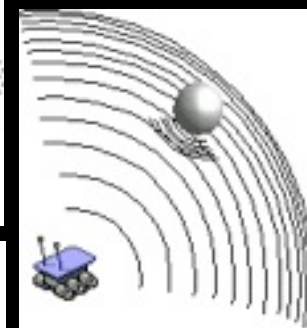
However to be processed for a microprocessor or PC, most signals are converted into a format suitable for digital systems, using for instance an Analog to Digital converter (A/D converter).

Concepts (4)

Sensors can also be passive or active:

Passive sensors only receive signals, e.g. a photoresistor or light sensor.

Active sensors emit energy that is reflected by external objects and measure the returned energy, e.g. a camera equipped with a flash, an ultrasonic sensor.



Concepts (5)

Passive sensors are non-intrusive and tightly dependent on environmental conditions, whereas active sensors are intrusive and can affect the conditions upon which a stimuli is measured.

Intrusiveness is a **major concern** when measuring parameters of **living organisms**.

Concepts (6)

Sensors can also be classified as inner or outer sensors.

Inner or proprioceptive sensors measure the own individual parameters of the holder, e.g. position of its joints, level of its battery, etc.

Outer or external sensors measure parameters of the holder's surrounding area, e.g. humidity, color of objects, etc. These can also be classified as contact and non-contact sensors, e.g. switches and video-cameras, respectively.

Concepts (7)

Range or field of view (fov): the set of values of a physical stimuli to which a sensor is able to react, e.g. $-10^0 - 50^0$, 0 - 5kg.

Sensitivity: a measure of the degree of variation in the signal returned by a sensor according to changes of the physical stimuli that is measured, e.g. 1^0 , 1 gr.

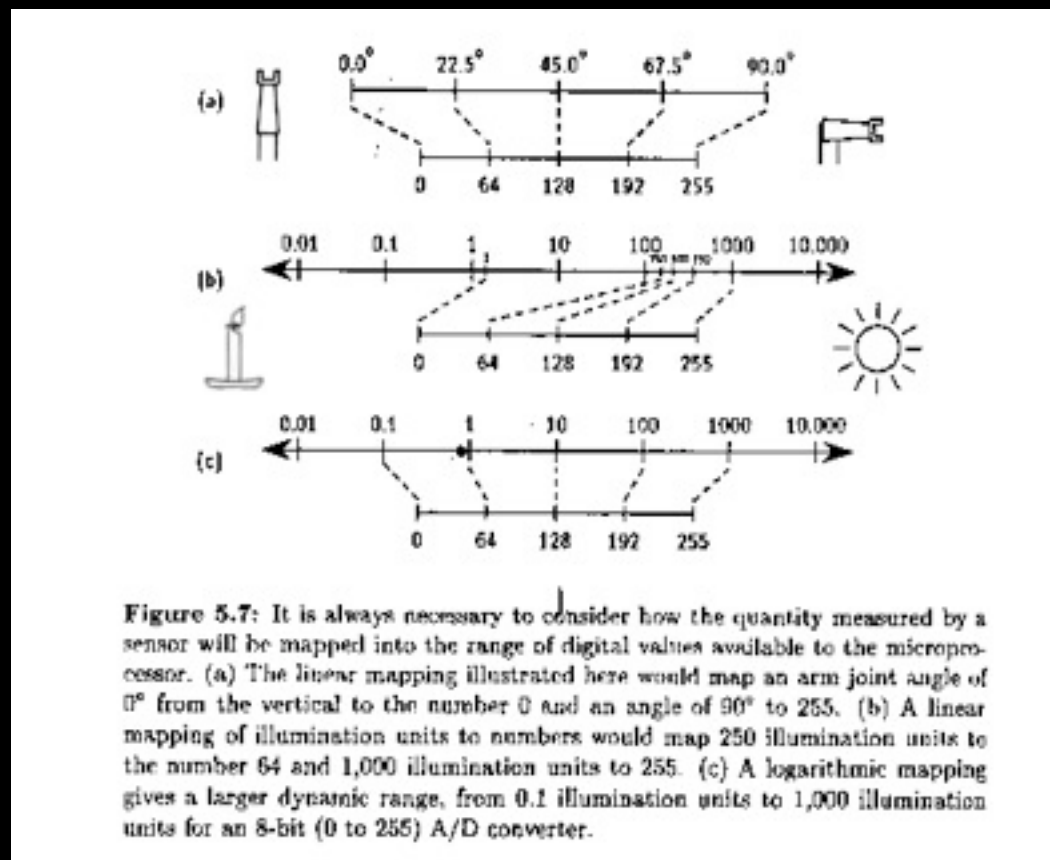
Concepts (8)

Noise and **artifacts**: abnormalities, non-sense or unwanted information produced by interferences when measuring or transmitting a signal.

Concepts (9)

The quality of the output of a sensor depends on the manner as the physical stimuli is transformed into digital values.

Examples of de transformations for an 8-bit processor (Jones & Flynn, 1999).



Concepts (10)

“Mood devices”

The operation of physical sensors might be affected by various factors, such as power supply, natural lightning, temperature/humidity of the environment, magnetic materials, etc.

Consult datasheet to know the average sensor’s performance documented by the designer and to know how much you can trust a sensor!



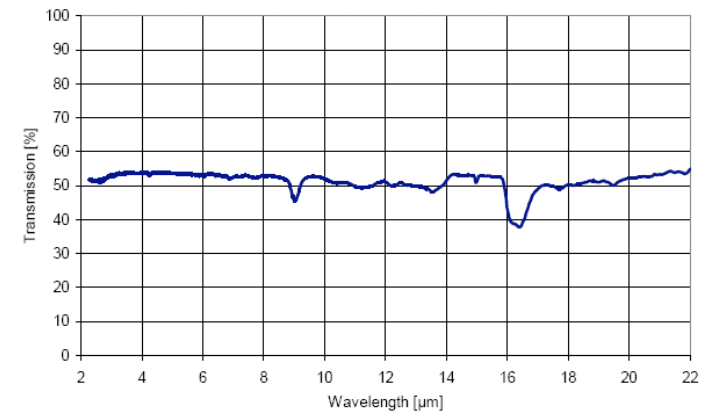
TPA81 Thermopile Array
Technical Specification

Introduction

The TPA81 is a thermopile array detecting infra-red in the 2 μ m-22 μ m range. This is the wavelength of radiant heat. The Pyro-electric sensors that are used commonly in burglar alarms and to switch on outside lights, detect infra-red in the same waveband. These Pyro-electric sensors can only detect a change in heat levels though - hence they are movement detectors. Although useful in robotics, their applications are limited as they are unable to detect and measure the temperature of a static heat source. Another type of sensor is the thermopile array. These are used in non-contact infra-red thermometers. They have a very wide detection angle or field of view (FOV) of around 100° and need either shrouding or a lens or commonly both to get a more useful FOV of around 12°. Some have a built in lens. More recently sensors with an array of thermopiles, built in electronics and a silicon lens have become available. This is the type used in the TPA81. It has an array of eight thermopiles arranged in a row. The TPA81 can measure the temperature of 8 adjacent points simultaneously. The TPA81 can also control a servo to pan the module and build up a thermal image. The TPA81 can detect a candle flame at a range 2 metres (6ft) and is unaffected by ambient light!

Spectral Response

The response of the TPA81 is typically 2 μ m to 22 μ m and is shown below:



Field of View (FOV)

The typical field of view of the TPA81 is 41° by 6° making each of the eight pixels 5.12° by 6°. The array of eight pixels is orientated along the length of the PCB - that's from top to bottom in the diagram below. Pixel number one is nearest the tab on the sensor - or at the bottom in the diagram below.

Sensitivity

Here's some numbers from one of our test modules:

For a candle, the numbers for each of the eight pixels at a range of 1 meter in a cool room at 12°C are: 11 10 11 12 12 29 15 13 (All °C)

You can see the candle showing up as the 29°C reading. At a range of 2 meters this reduces to 20°C -

Parameter	Specification	Unit	Condition
Carrier Type	TO18		
Housing	TO18		
Element Size	2.5 x 1	mm	
Spacing	1	mm	
Responsivity	Min 5.2	V/°C	T: 30°C, RH: 50%
	Typ 6.0		(One element only)
Nonlinearity	Max ±10	%	T: 30°C, RH: 50%
			(All element array)
Noise	Typ 20	μV/°C	20°C, 50% RH
	Max 30		
Operating Voltage	Min 0.2	V	Non-ETIC
	Max 1.5		
Window Material	Black anodized		
Operational Temperature Range	See note	°C	T: 30°C
	Min -40		
	Max 85		
Operating Voltage	5V	V	Typical
Supply Current	15	mA	
Storage Temperature	-40 to 85	°C	



Finding patterns



Finding patterns (1)

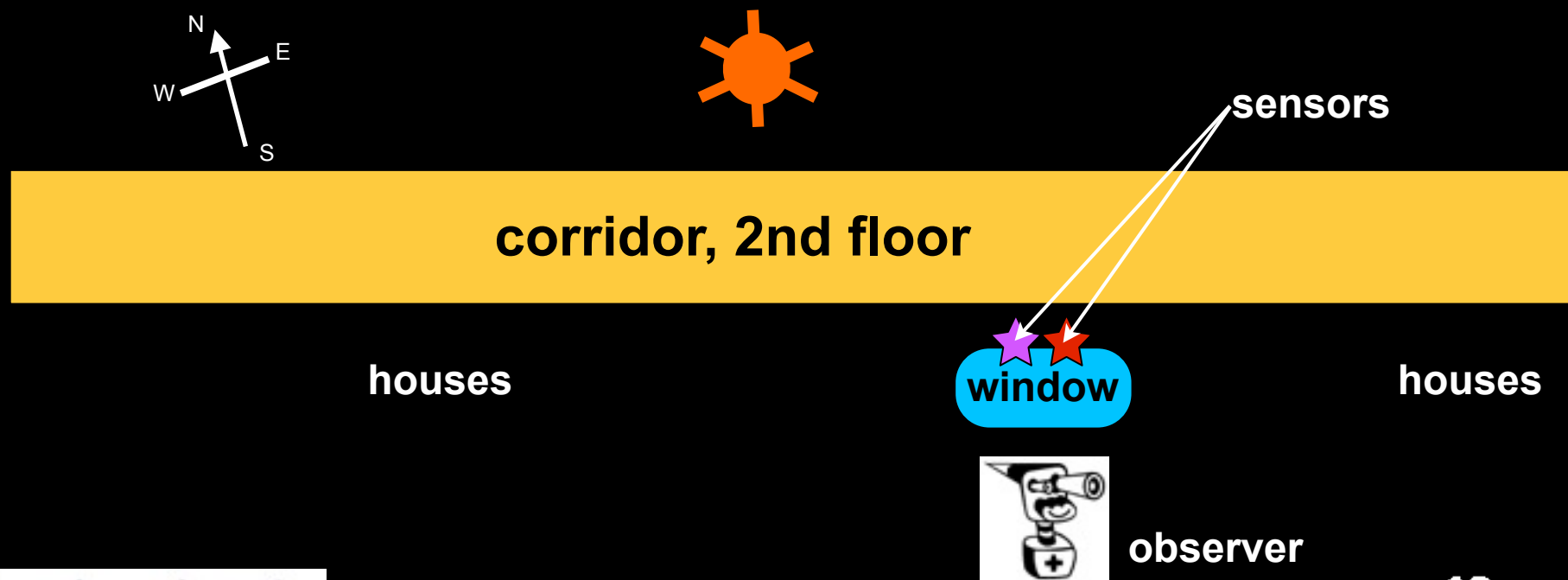
How can we exploit the information provided by a sensor?

How can we associate raw readings with events of interest?

How can we identify **patterns/regularities** in data sets related to “soft phenomena” (human actions, human parameters, etc.) that are by definition uncertain, incomplete and noisy?

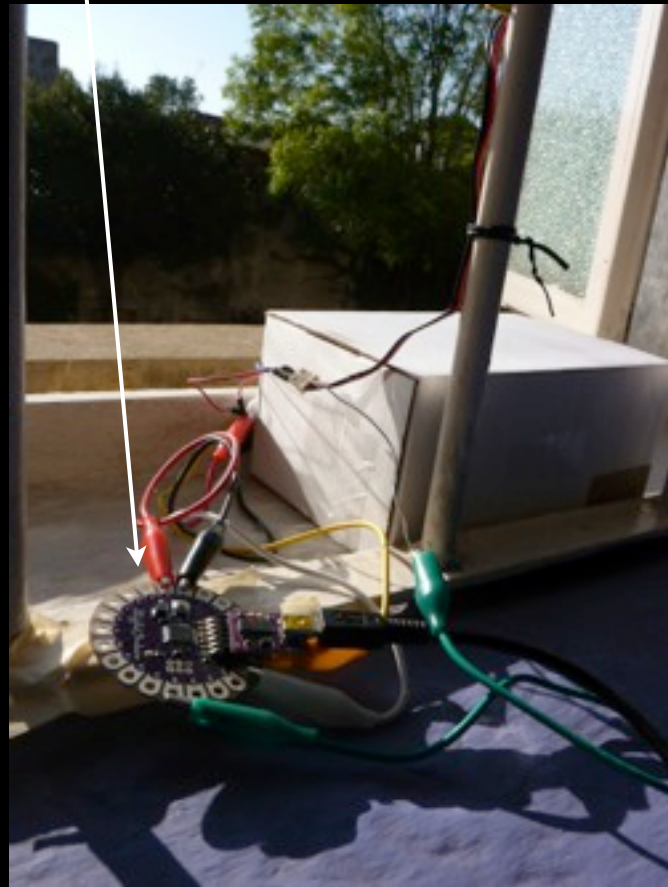
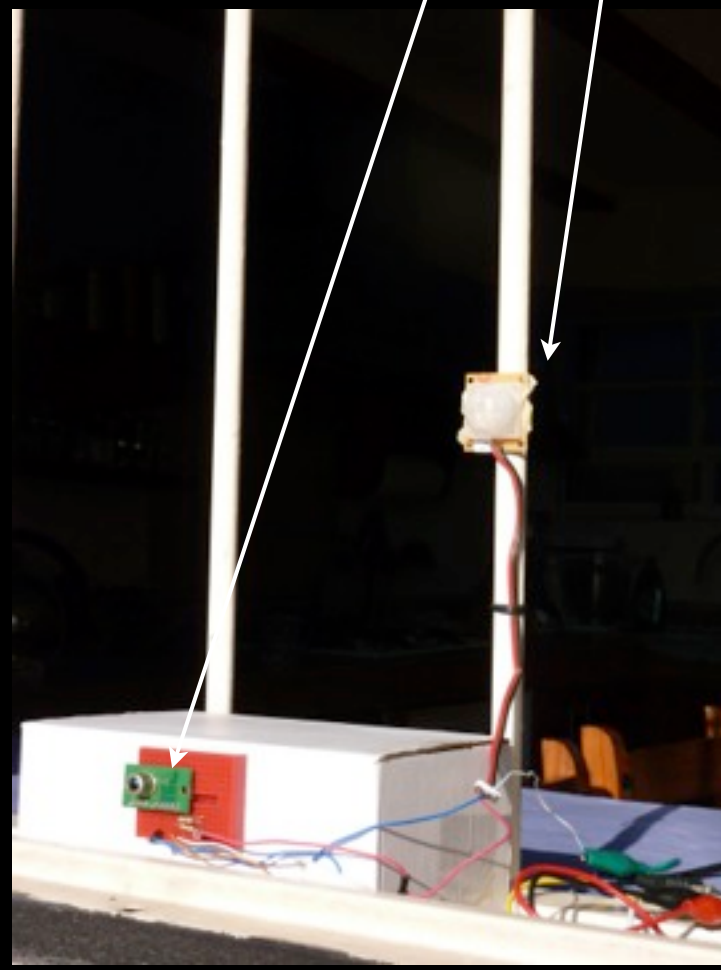
Finding patterns (2)

A naive experiment: counting people that traverse a corridor in two senses using cheap and discrete sensors.



Finding patterns (3)

- 1 TPA81 thermopile array from Devantech,
- 1 SE-10 motion sensor,
- 1 Lilypad main board (ATMega 328) from Arduino.



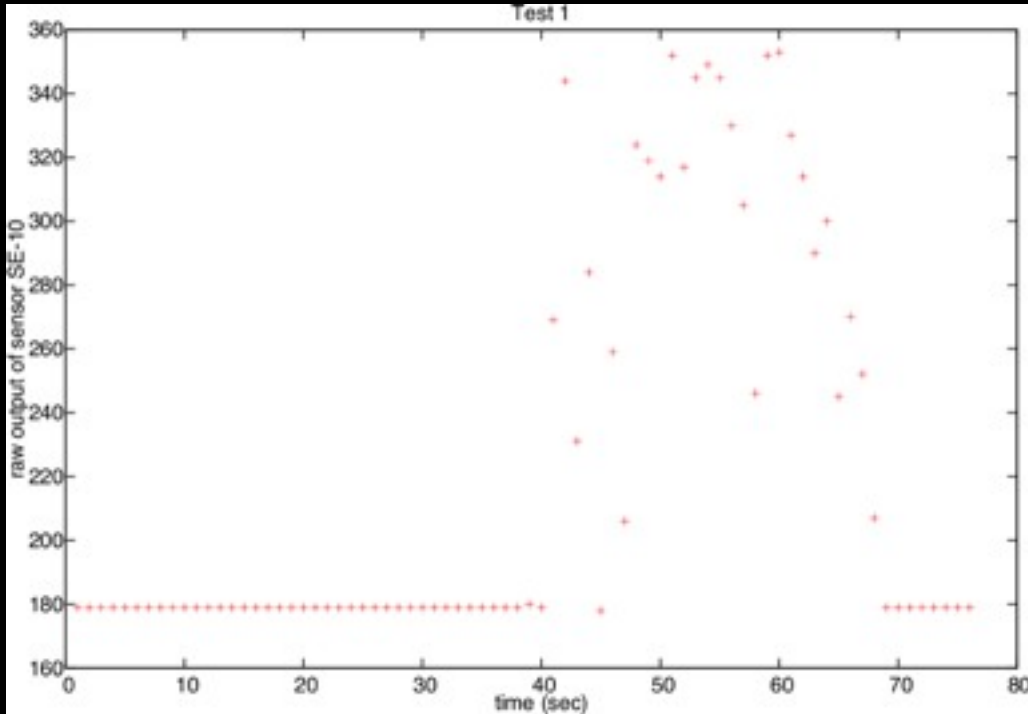
Experimental setup: back ↑,

front ↑

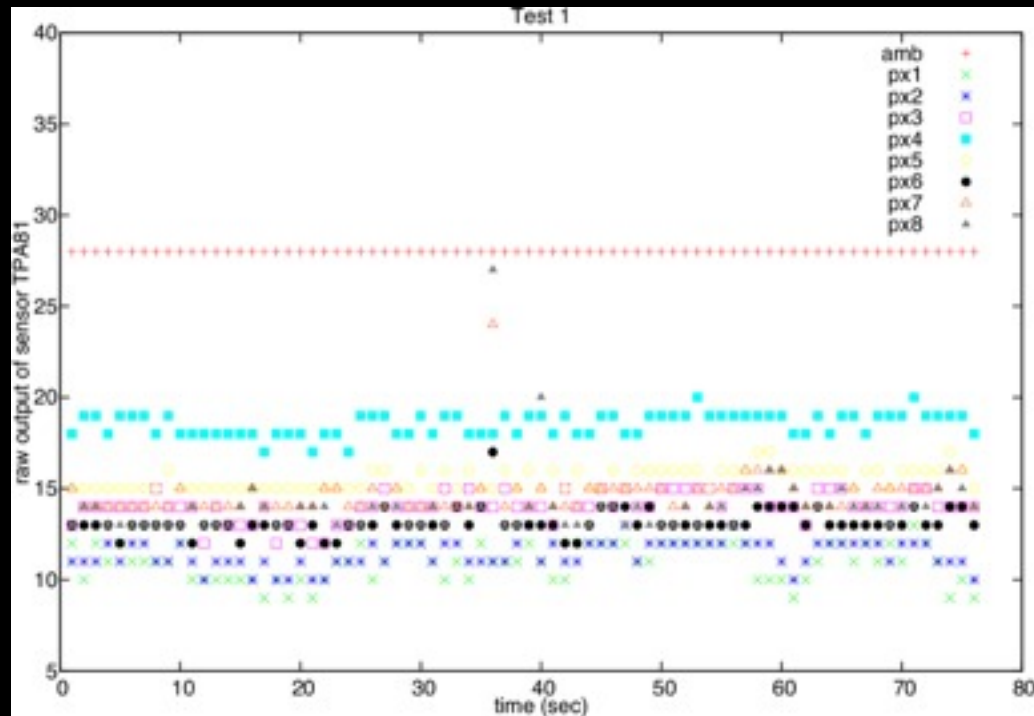
and main board →



Finding patterns (4)



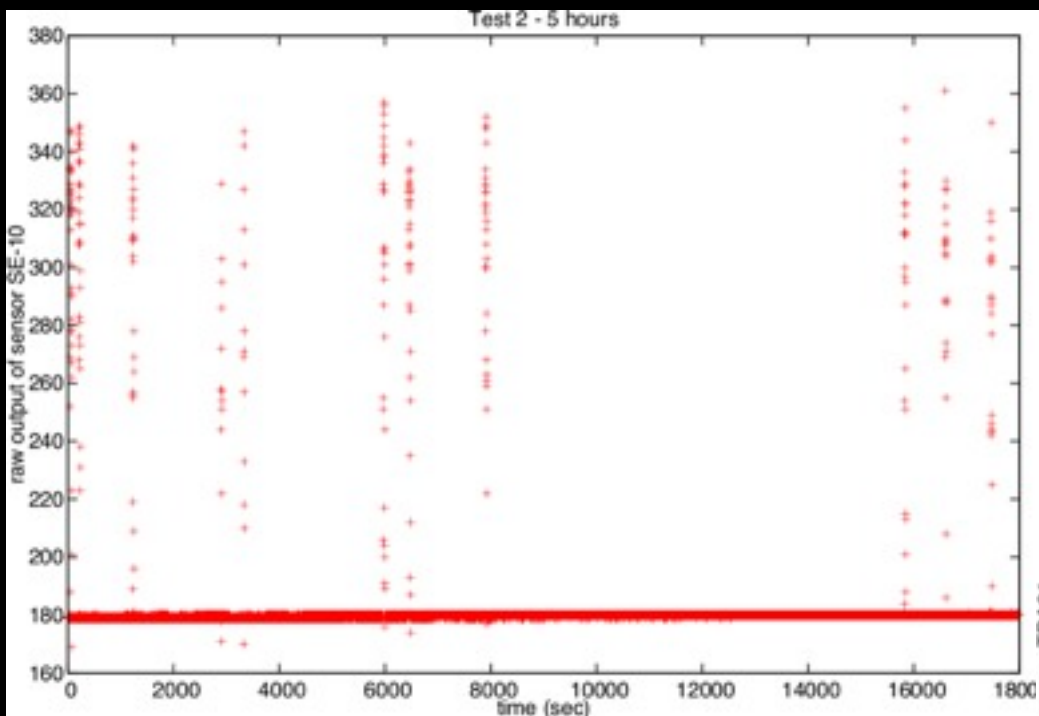
Raw output from
← SE-10 sensor and
TPA81 sensor ↓



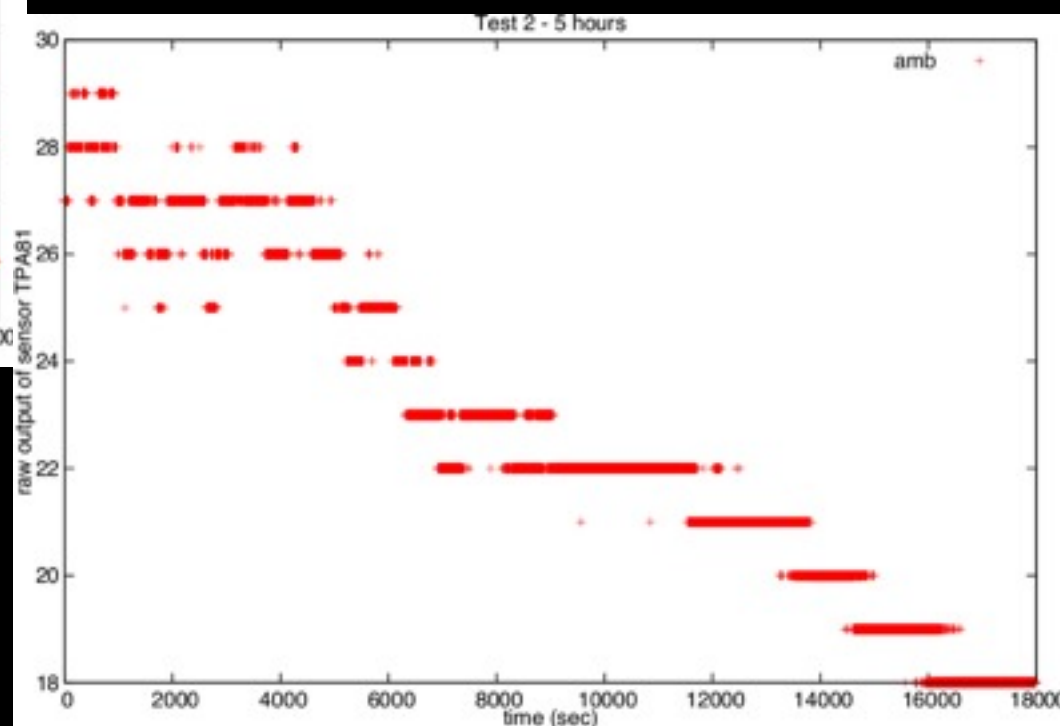
Test1: 1'20", one person traversed the corridor from left to right, and then from right to left.
1 record each second.



Finding patterns (5)



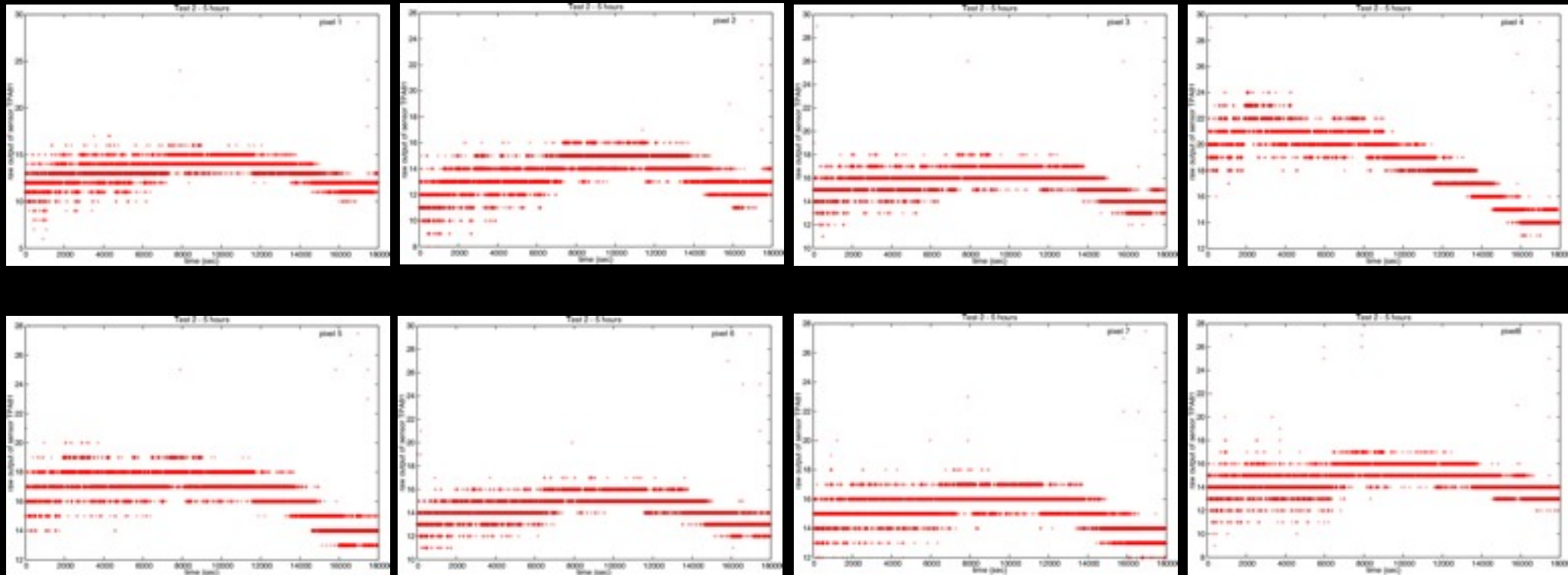
Raw output from
← SE-10 sensor and
ambient pixel of TPA81 sensor ↓



Test2: 5 hours (1:45 pm - 6:45 pm)
several persons traversed the
corridor in both senses.
1 record each second.

Finding patterns (6)

Test2: 5 hours (1:45 pm - 6:45 pm)
several persons traversed the
corridor in both senses.
1 record each second.

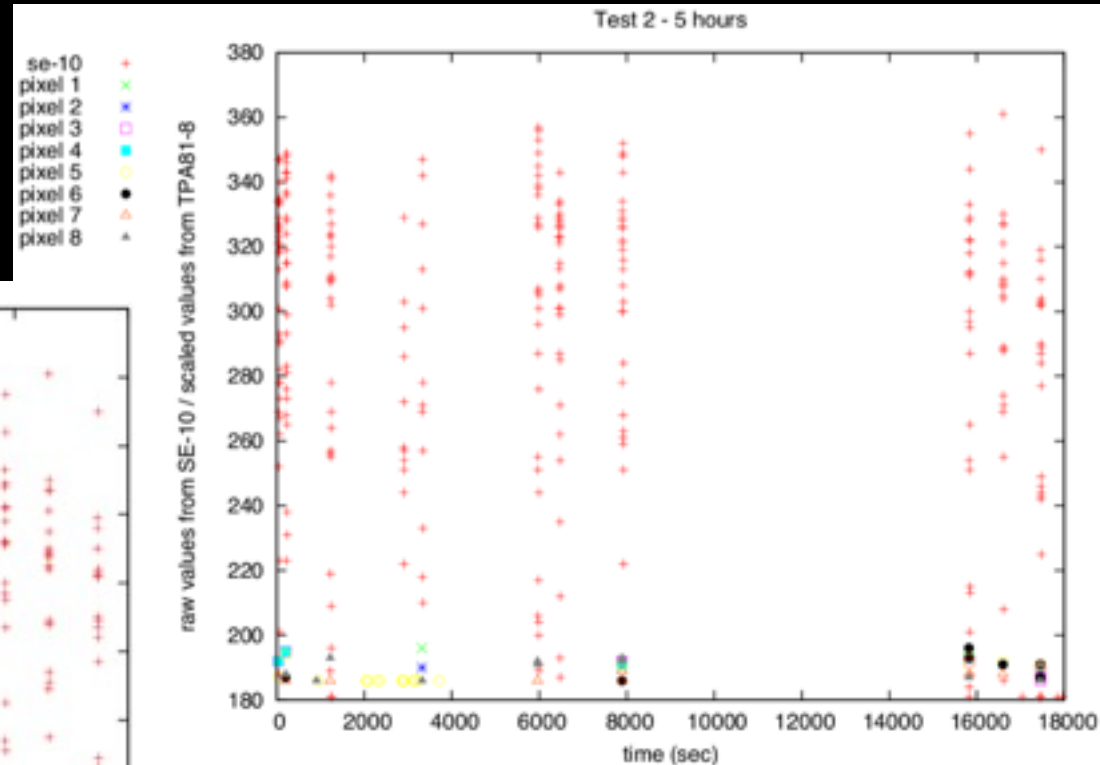
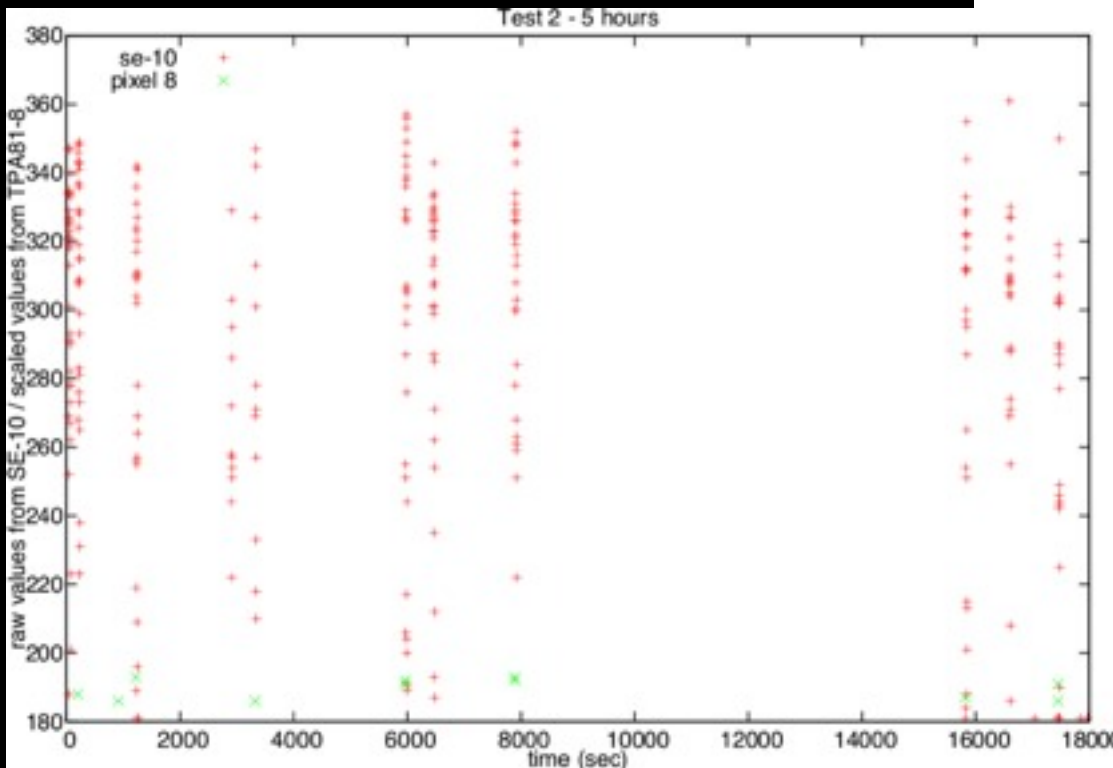


↑ Test2: Raw output from pixel1 to pixel8 of TPA81 sensor, from left-top figure to right-bottom figure.



Finding patterns (7)

Scaling and matching
↓ two and nine →
“evidences”



Test2: 5 hours (1:45 pm - 6:45 pm)
several persons traversed the
corridor in both senses.
1 record each second.

Finding patterns (8)

Test2: 5 hours (1:45 pm - 6:45 pm)
 several persons traversed the corridor in both senses. 1 record each second.

People can be detected from periods or rows of high values

	A	B	C	D	E	F	G	H	I	J	K	L	M
32	31	0:00:30	179	27	30	10	14	18	15	13	15	14	
33	32	0:00:31	179	27	11	10	14	18	15	13	14	14	
34	33	0:00:32	179	27	12	12	14	19	15	13	15	15	
35	34	0:00:33	179	27	11	11	14	19	16	13	14	13	
36	35	0:00:34	179	27	11	11	14	19	15	13	15	14	
37	36	0:00:35	179	27	13	18	26	26	18	13	15	14	1
38	37	0:00:36	179	27	11	11	14	18	16	14	14	14	
39	38	0:00:37	179	27	11	13	19	20	21	19	16	14	
40	39	0:00:38	180	27	11	10	14	18	15	13	15	14	
41	40	0:00:39	252	27	11	10	14	19	16	13	14	13	
42	41	0:00:40	188	27	12	11	14	19	16	13	15	14	
43	42	0:00:41	180	27	12	12	14	18	16	13	14	14	
44	43	0:00:42	269	27	11	11	14	18	15	12	14	14	
45	44	0:00:43	347	27	12	11	15	20	16	14	15	14	
46	45	0:00:44	321	27	12	11	15	19	16	14	14	14	
47	46	0:00:45	334	27	12	11	14	19	16	13	13	13	
48	47	0:00:46	334	27	11	11	15	19	16	13	15	14	
49	48	0:00:47	329	27	11	11	15	19	16	13	14	13	
50	49	0:00:48	327	27	12	11	14	19	16	14	15	13	
51	50	0:00:49	325	27	12	11	14	19	16	14	15	14	
52	51	0:00:50	321	27	12	13	14	20	16	13	15	14	
53	52	0:00:51	318	27	12	11	14	19	16	13	15	14	
54	53	0:00:52	313	27	12	11	15	20	16	13	14	14	
55	54	0:00:53	301	27	12	11	14	19	16	13	14	13	
56	55	0:00:54	326	27	11	12	14	19	16	13	14	13	
57	56	0:00:55	335	27	12	12	15	19	16	13	15	13	
58	57	0:00:56	323	27	12	12	14	19	16	14	14	14	
59	58	0:00:57	278	27	12	12	15	18	17	13	15	14	
60	59	0:00:58	291	27	11	11	14	19	16	14	14	13	
61	60	0:00:59	333	27	12	12	14	19	16	13	15	14	
62	61	0:01:00	293	27	11	11	15	19	16	13	14	14	
63	62	0:01:01	319	27	12	11	15	20	16	13	16	15	
64	63	0:01:02	278	27	11	13	14	19	16	13	14	13	
65	64	0:01:03	273	28	13	12	16	20	17	14	15	14	
66	65	0:01:04	347	27	12	12	14	19	16	13	15	13	
67	66	0:01:05	340	27	12	11	14	19	15	13	15	13	
68	67	0:01:06	282	28	13	13	16	20	16	14	15	14	
69	68	0:01:07	267	28	12	13	15	20	16	14	15	15	
70	69	0:01:08	290	28	13	12	15	20	17	14	16	14	
71	70	0:01:09	262	28	13	12	16	20	17	15	16	15	
72	71	0:01:10	223	28	12	13	16	20	17	14	15	15	
73	72	0:01:11	201	28	13	13	15	20	16	14	15	14	
74	73	0:01:12	169	28	12	12	15	20	16	14	15	15	
75	74	0:01:13	179	28	12	12	15	20	17	13	16	14	
76	75	0:01:14	179	28	13	12	16	20	17	14	15	14	
77	76	0:01:15	179	28	12	11	15	20	16	14	14	14	

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
17441	17440	4:53:28	180	18	11	13	14	15	14	13	13	13	13		
17442	17441	4:53:29	180	18	12	13	14	15	14	13	13	13	13		
17443	17442	4:53:30	180	18	12	12	14	15	14	13	13	13	13		
17444	17443	4:53:31	180	18	11	13	14	14	14	13	14	13	13		
17445	17444	4:53:32	180	18	12	13	14	15	14	14	13	13	13		
17446	17445	4:53:33	180	18	12	13	13	15	14	13	13	13	13		
17447	17446	4:53:34	180	18	12	12	14	14	14	13	14	14	14		
17448	17447	4:53:35	180	18	12	13	14	15	14	13	14	13	13		
17449	17448	4:53:36	180	18	11	13	14	15	14	13	13	13	13		
17450	17449	4:53:37	180	18	11	13	14	14	14	14	14	13	13		
17451	17450	4:53:38	180	18	18	21	23	22	23	21	19	20	14	14	14
17452	17451	4:53:39	180	18	13	17	21	23	25	25	25	25	25	14	14
17453	17452	4:53:40	180	18	23	22	20	16	16	13	15	14	14	14	14
17454	17453	4:53:41	180	18	12	13	15	15	15	14	14	13	13	13	13
17455	17454	4:53:42	181	18	12	13	15	14	14	14	14	13	13	13	13
17456	17455	4:53:43	181	18	12	12	14	14	14	14	14	13	13	13	13
17457	17456	4:53:44	181	18	12	12	14	14	14	14	14	13	13	13	13
17458	17457	4:53:45	319	18	12	14	15	15	14	13	13	13	13	13	13
17459	17458	4:53:46	302	18	11	13	14	14	14	13	13	13	13	13	13
17460	17459	4:53:47	316	18	11	13	14	14	14	13	13	13	13	13	13
17461	17460	4:53:48	310	18	12	13	14	14	14	13	13	13	13	13	13
17462	17461	4:53:49	303	18	12	13	15	15	14	13	13	13	13	13	13
17463	17462	4:53:50	302	18	11	12	14	14	13	14	13	13	13	13	13
17464	17463	4:53:51	290	18	11	13	14	14	14	13	13	13	13	13	13
17465	17464	4:53:52	287	18	12	13	14	15	14	13	13	13	13	13	13
17466	17465	4:53:53	242	18	12	13	14	15	13	13	13	13	13	13	13
17467	17466	4:53:54	284	18	11	13	14	14	14	14	14	12	12	12	12
17468	17467	4:53:55	246	18	11	12	14	15	14	13	13	13	13	13	13
17469	17468	4:53:56	243	18	11	13	15	14	14	13	13	13	13	13	13
17470	17469	4:53:57	350	18	12	12	15	14	13	13	13	13	13	13	13
17471	17470	4:53:58	304	18	11	13	13	14	14	14	12	12	12	12	12
17472	17471	4:53:59	289	18	11	13	14	14	14	14	13	13	13	13	13
17473	17472	4:54:00	249	18	11	12	15	14	15	13	13	13	13	13	13
17474	17473	4:54:01	277	18	11	13	14	15	14	13	13	13	13	13	13
17475	17474	4:54:02	244	18	11	13	14	14	14	13	13	13	13	13	13
17476	17475	4:54:03	225	18	12	13	14	14	14	13	13	13	13	13	13
17477	17476	4:54:04	190	18	12	13	14	14	13	13	13	13	13	13	13
17478	17477	4:54:05	180	18	11	13	14	14	13	14	13	13	13	13	13
17479	17478	4:54:06	180	18	12	13	14	15	14	13	13	13	13	13	13
17480	17479	4:54:07	180	18	11	12	15	14	14	13	13	13	13	13	13
17481	17480	4:54:08	180	18	11	13	14	14	14	13	13	13	13	13	13
17482	17481	4:54:09	180	18	12	13	15	14	14	13	13	13	13	13	13
17483	17482	4:54:10	180	18	12	13	14	14	14	13	13	13	13	13	13
17484	17483	4:54:11	180	18	12	13	15	14	14	13	13	13	13	13	13
17485	17484	4:54:12	180	18	12	13	14	14	15	13	13	13	13	13	13
17486	17485	4:54:13	180	18	11	13	14	14	14	13	13	13	13	13	13
17487	17486	4:54:14	180	18	11	13	14	14	14	13	13	13	13	13	13
17488	17487	4:54:15	180	18	11	13	14	14	14	13	13	13	13	13	13
17489	17488	4:54:16	180	18	11	13	14	14	14	13	13	13	13	13	13
17490	17489	4:54:17	180	18	12	12	14	14	14	13	13	13	13	13	13
17491	17490	4:54:18	180	18	12	12	14	14	14	13	13	13	13	13	13
17492	17491	4:54:19	180	18	12	12	14	14	14	13	13	13	13	13	13
17493	17492	4:54:20	180	18	11	13	15	14	14	13	13	13	13	13	13
17494	17493	4:54:21	180	18	11	12	15	14	14	13	13	13	13	13	13
17495	17494	4:54:22	180	18</											

Finding patterns (9)

	B	C	D	E	F	G	H	I	J	K	L	M	N	O
2890	0:48:36	179	26	13	14	16	22	18	14	15	14			
2891	0:48:37	179	27	15	15	18	23	19	15	17	16			
2892	0:48:38	179	27	15	14	16	23	19	16	17	15			
2893	0:48:39	179	27	13	14	17	23	18	16	16	15			
2894	0:48:40	179	27	14	15	18	23	19	15	17	15			
2895	0:48:41	179	27	14	14	17	22	18	15	16	15			
2896	0:48:42	179	27	14	14	17	23	19	15	16	15			
2897	0:48:43	179	26	12	13	16	22	17	14	15	15			
2898	0:48:44	180	27	15	15	17	23	19	15	16	16			
2899	0:48:45	180	26	13	14	16	22	18	15	15	14			
2900	0:48:46	180	27	15	14	17	23	19	15	16	16			
2901	0:48:47	180	27	14	15	17	22	19	16	17	15			
2902	0:48:48	180	27	14	15	17	23	19	16	16	15			
2903	0:48:49	258	27	15	14	16	23	18	15	17	15			
2904	0:48:50	180	27	15	14	17	22	19	16	16	15			
2905	0:48:51	244	27	14	14	16	23	19	15	16	15			
2906	0:48:52	178	27	14	15	16	23	20	15	16	17			
2907	0:48:53	171	27	13	14	17	23	19	15	17	16			
2908	0:48:54	272	27	13	13	17	22	18	15	15	16			
2909	0:48:55	222	27	13	14	16	22	19	15	17	16			
2910	0:48:56	180	27	13	14	16	22	19	14	15	16			
2911	0:48:57	329	27	15	14	16	22	19	15	16	16			
2912	0:48:58	286	27	13	14	16	22	19	15	15	15			
2913	0:48:59	303	27	13	13	17	22	17	15	16	15			
2914	0:49:00	257	27	13	14	17	22	19	15	16	15			
2915	0:49:01	295	27	13	14	16	22	18	15	17	15			
2916	0:49:02	254	27	15	13	17	22	19	15	16	15			
2917	0:49:03	251	27	14	14	16	22	18	15	16	15			
2918	0:49:04	180	27	13	14	17	22	18	15	16	15			
2919	0:49:05	179	27	13	14	17	23	18	16	16	16			
2920	0:49:06	179	27	14	14	17	22	19	15	16	15			
2921	0:49:07	179	27	13	14	16	22	18	15	16	16			
2922	0:49:08	179	27	13	14	17	23	18	15	17	15			
2923	0:49:09	179	27	14	14	16	22	19	16	17	15			
2924	0:49:10	179	27	13	15	17	22	18	16	17	16			
2925	0:49:11	179	27	14	14	17	22	18	15	17	15			
2926	0:49:12	180	27	14	15	17	22	19	15	16	16			
2927	0:49:13	179	27	14	14	16	22	19	15	16	16			
2928	0:49:14	179	27	14	15	16	22	18	15	16	15			
2929	0:49:15	179	27	13	14	17	21	18	14	16	15			
2930	0:49:16	179	27	15	14	16	22	18	15	16	15			
2931	0:49:17	180	27	14	14	17	22	18	15	15	14			
2932	0:49:18	179	27	14	14	16	21	18	15	16	15			
2933	0:49:19	179	27	14	14	16	22	19	15	16	15			
2934	0:49:20	179	27	15	14	16	22	18	15	16	14			
2935	0:49:21	179	27	13	14	17	21	18	15	16	15			

Test2: 5 hours (1:45 pm - 6:45 pm) several persons traversed the corridor in both senses. 1 record each second.



Sometimes people are only detected by one sensor (SE-10), that is not by the way the most accurate sensor!



Finding patterns (10)

How is it possible that sometimes a poor sensor outperforms a highly accurate sensor?

Any idea?

Finding patterns (11)

Preliminary results based
 ↓ on previous regularities

SD-10	TPA-81	SD-10 & TPA-81	Ground truth
1	1	1	1 adult
1	1	1	1 adult
1	1	1	1 adult
1	0	1	1 kid
1	2	2	2 adults
1	2	2	2 adults
1	0	1	2 kids
1	3	3	3 adults
1	2	2	2 adults
1	1	1	1 adult
1	3	3	3 adults
Totals	11	16	18



Finding patterns (12)

There are many other techniques and filters to detect regularities in datasets of soft phenomena.

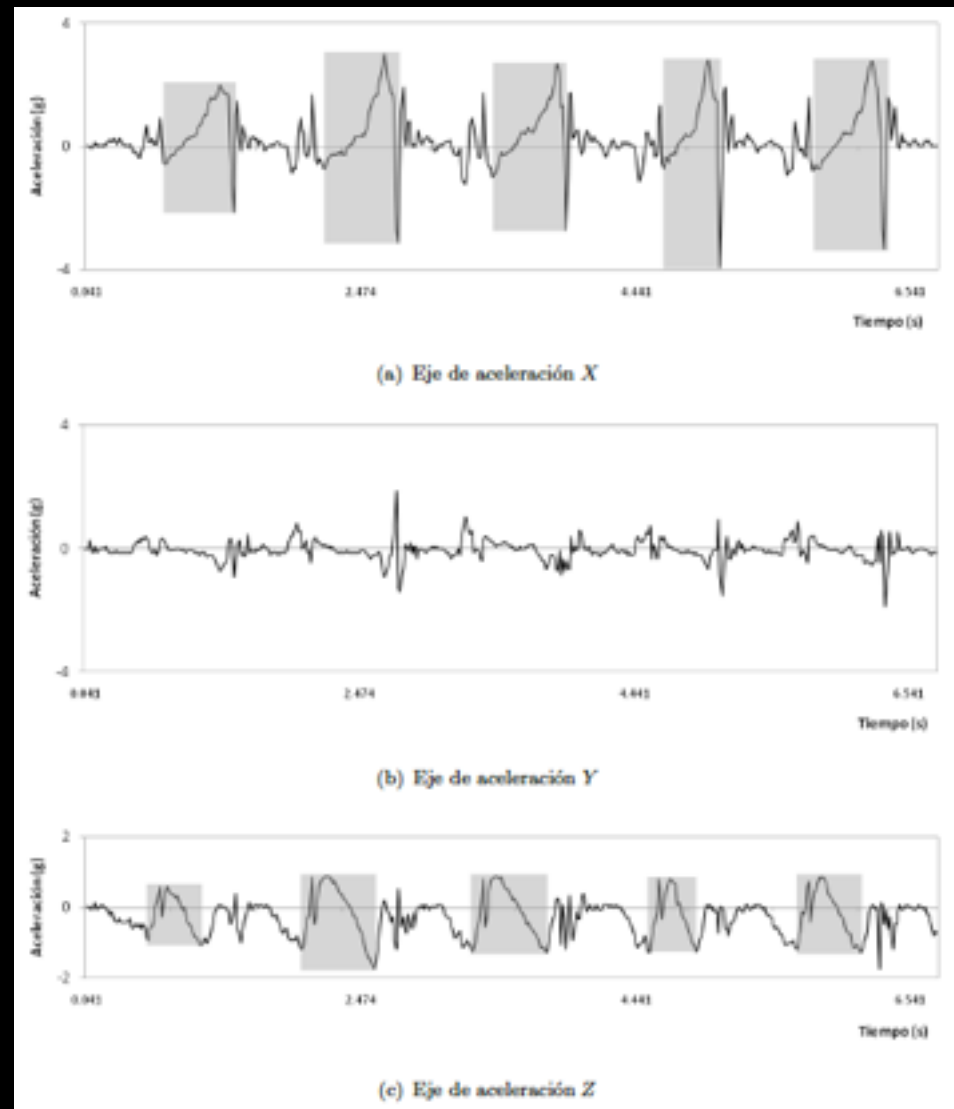
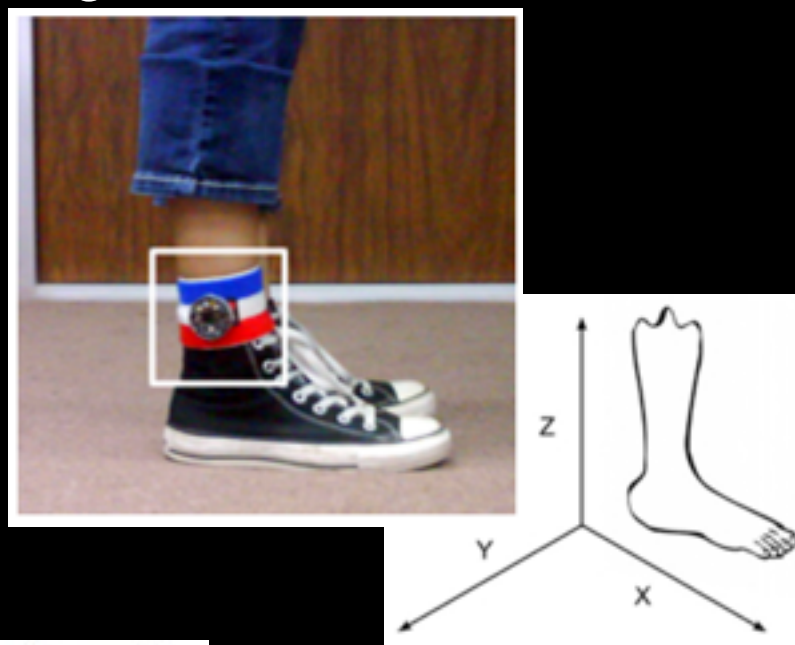
Some key ideas:

- combine & complement different sensors
- use reliable patterns based on dynamic/flexible thresholds or features of the sensor's signal.
- apply known filters, such as Kalman, particle filter, etc.
- apply machine learning algorithms.

Finding patterns (13)

Some examples used in our research

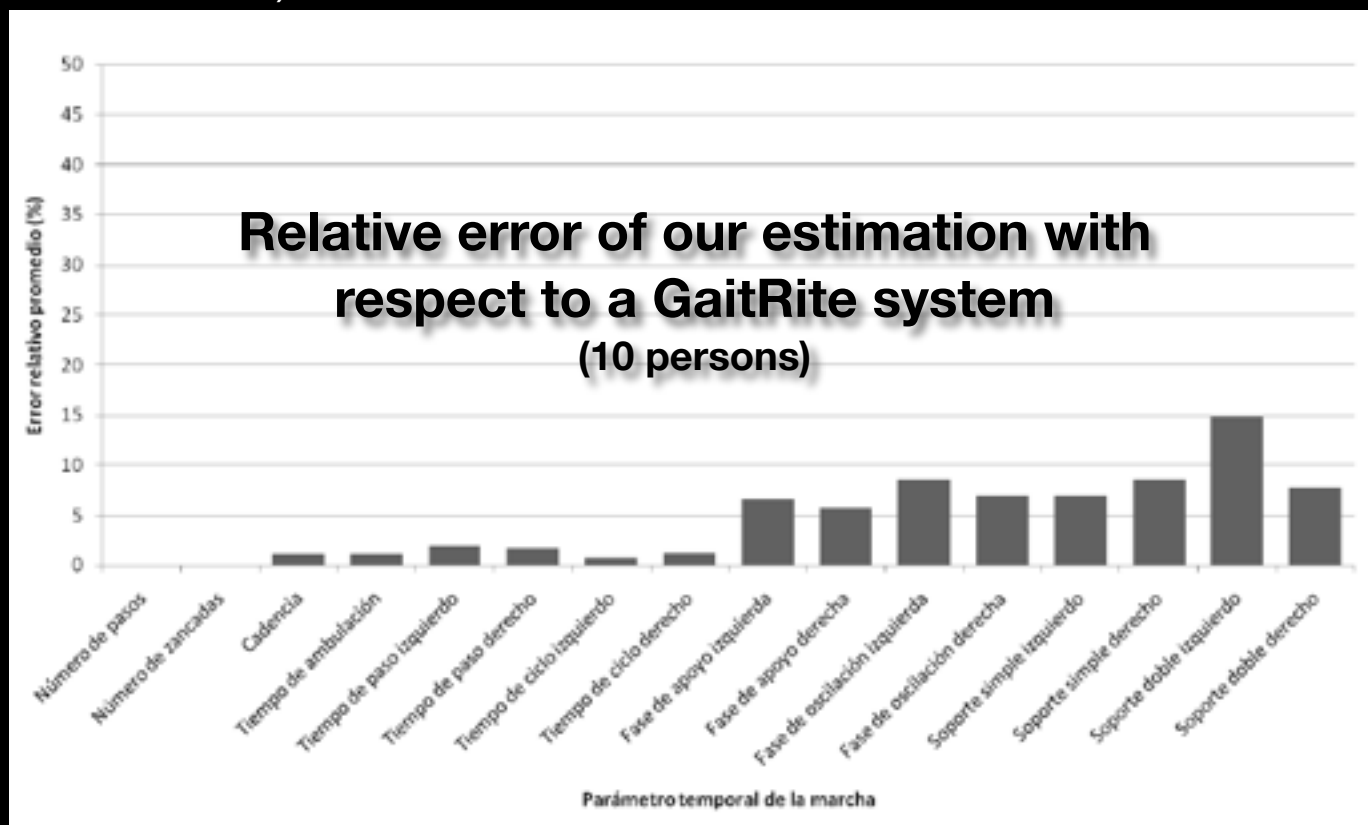
related characteristic peaks in two axis in acceleration signals for estimating parameters of the human gait.



Finding patterns (14)

Some examples used in our research

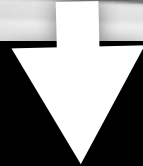
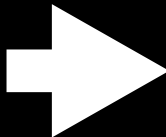
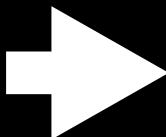
related characteristic peaks were competitive for estimating temporal parameters of the human gait using two wearable triaxial accelerometers (ZStar3 from Freescale, Austin, TX USA) under controlled conditions when compared to a GaitRite System (from CIR Industries, Clifton, NJ USA).



Finding patterns (15)

Some examples used in our research

features of intervals of acceleration signals, such as tendency, changes of area of gravity.



Resultados	
Resultado de la prueba: Hombro 1 hora 18/05/2013 01:21	
Reposo	88.8%
Actividad Moderada	8.8%
Actividad Intensa	2.5%
¡Casi no estuviste en movimiento!	

Resultados	
Resultado de la prueba: Hombro 1 hora 18/05/2013 24:36	
Reposo	61.2%
Actividad Moderada	0.0%
Actividad Intensa	38.8%
¡Bien, estuviste en movimiento!	

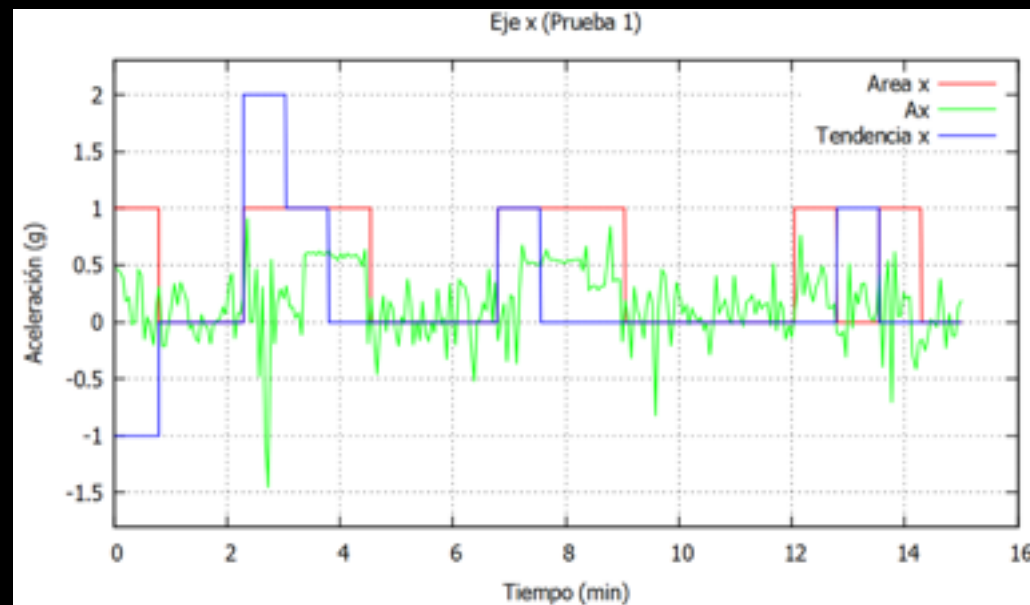
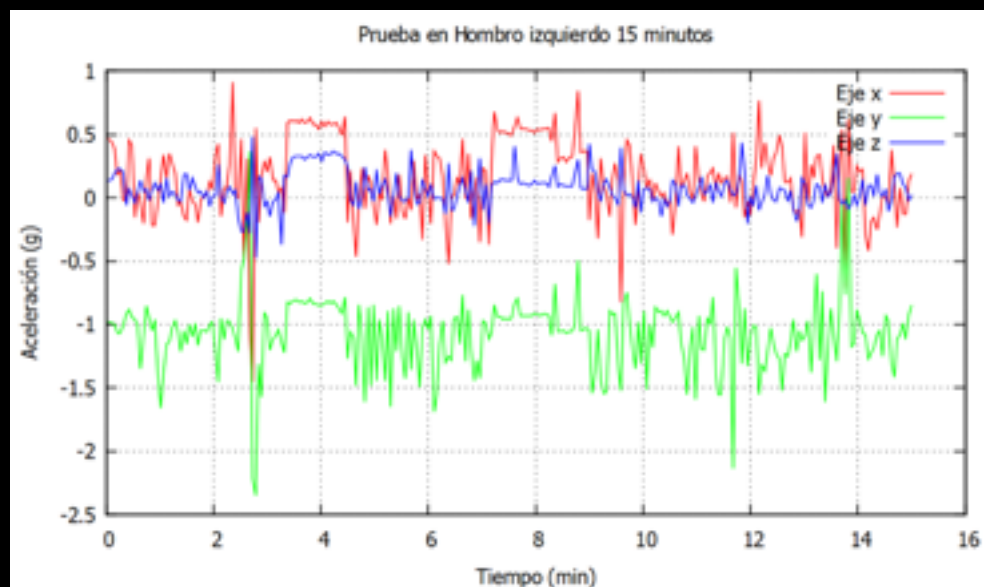
Resultados	
Resultado de la prueba: Hombro 1 hora 18/05/2013 24:57	
Reposo	28.8%
Actividad Moderada	41.2%
Actividad Intensa	30.0%
¡Perfecto, sigue así de activo!	



Finding patterns (16)

Some examples used in our research

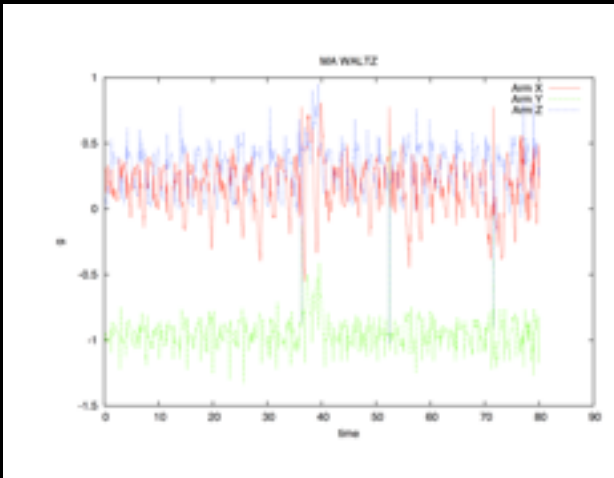
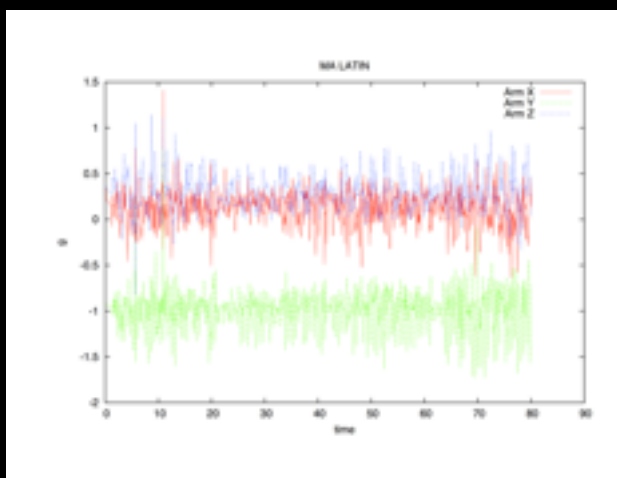
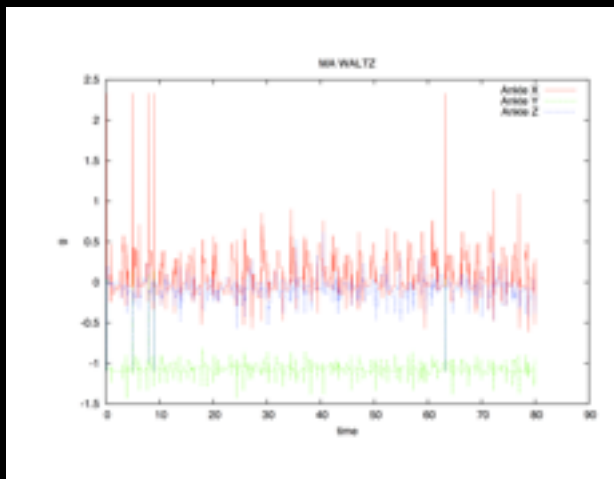
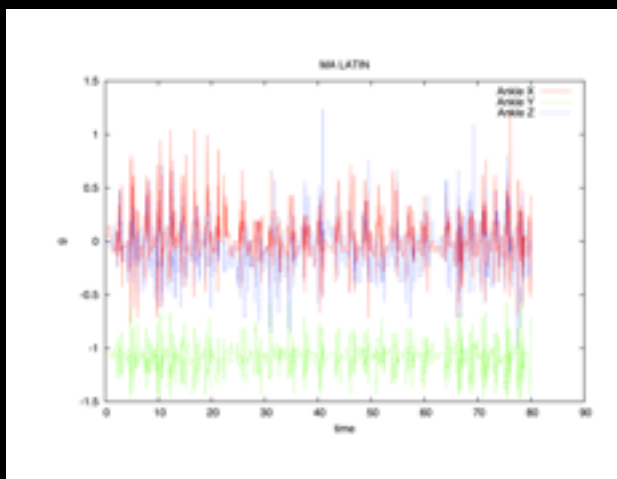
features of intervals of acceleration signals, such as tendency, changes of area of gravity.



Finding patterns (17)

Some examples used in our research

features of intervals of acceleration signals, such as tendency, changes of area of gravity.



Finding patterns (18)

Some examples
used in our research



Designing sensors



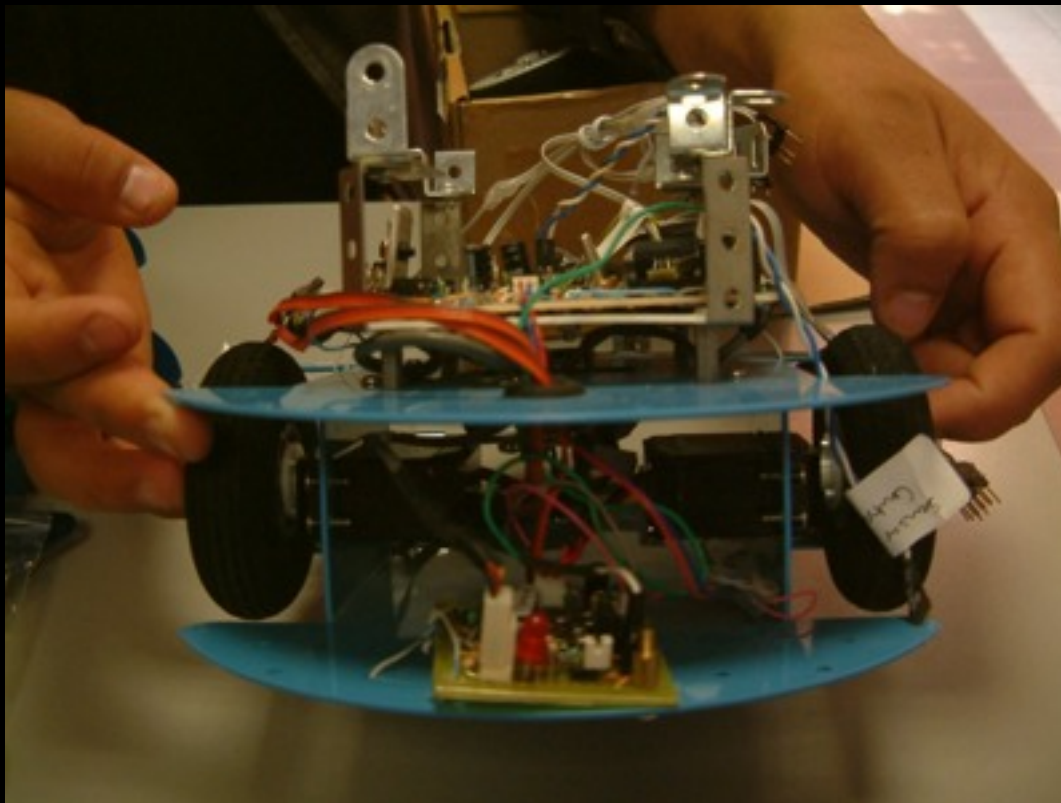
Designing your own sensors (1)

What if the sensor or module needed for your project doesn't exist or require a lot do-it-yourself work?

Consider to build or adapt yourself a module or sensor or consider to collaborate with other people to build it!

Designing your own sensors (2)

Hands-on experience in the design of sensors for micro mobile robots.



Local recognition on some elements of the environment and other robots. Each robot controlled by a Handyboard (MIT, Boston, USA) based on the chip 68HC11 from Motorola.

Main drawback:
limited processing capabilities

Designing your own sensors (3)

Hands-on experience in the design of sensors for micro mobile robots.

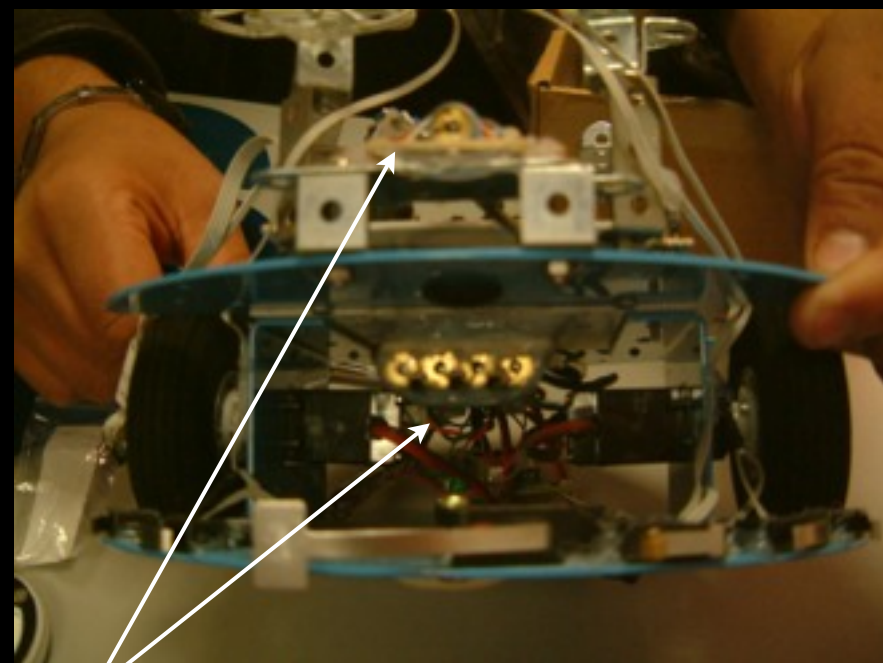
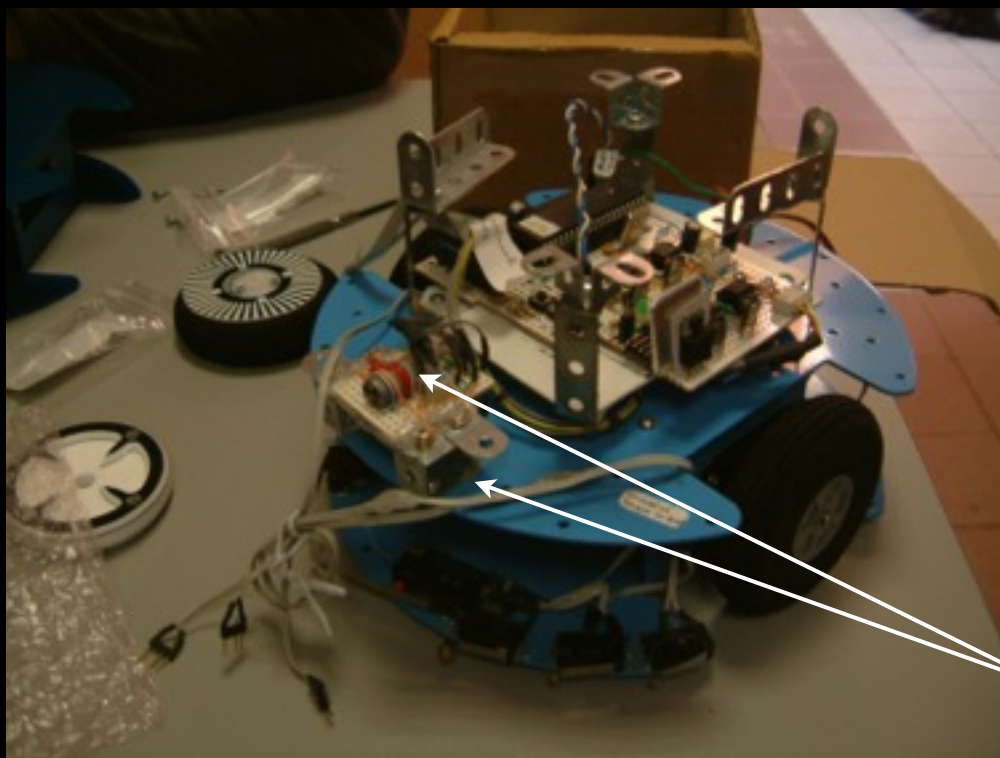


Bar code reader based on past experiences for the recognition of coded information in environmental landmarks and fiducial codes worn by robots.

The original system was developed for the MICROBRES project (University of Paris VI, Paris, France) between 2001-2003 and it relies on a CCD camera.

Designing your own sensors (4)

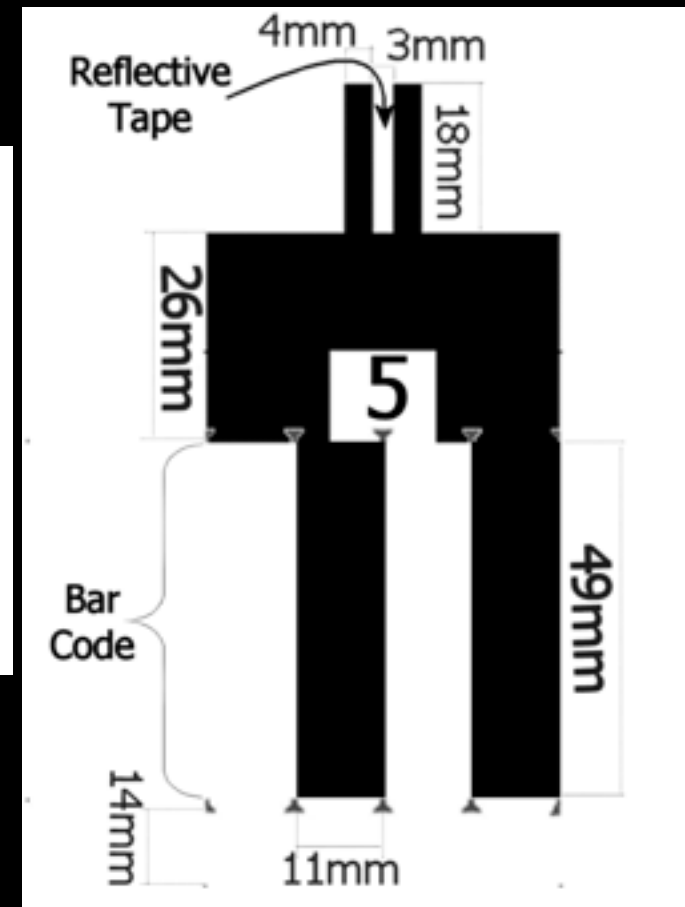
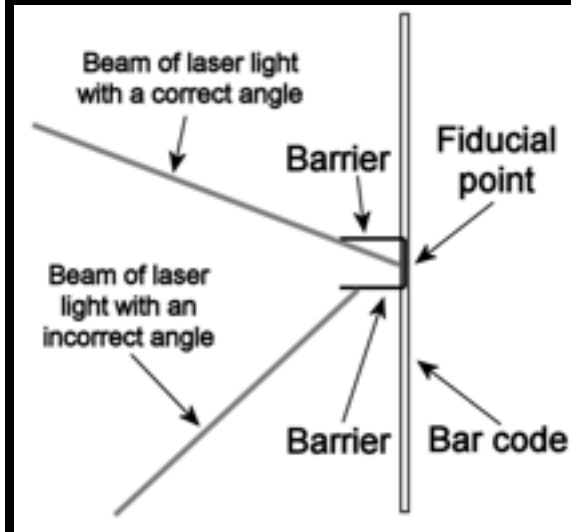
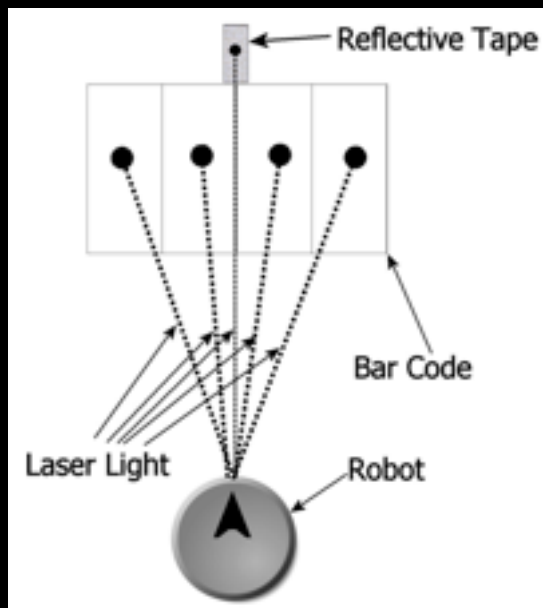
Hands-on experience in the design of sensors for micro mobile robots.



Active bar code reader of 4-bit landmarks.

Designing your own sensors (5)

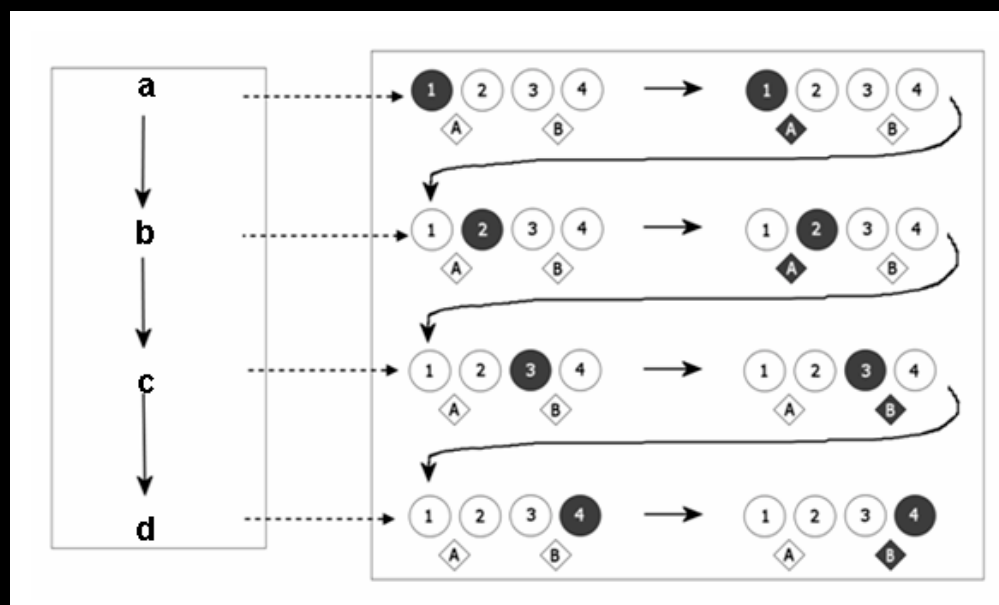
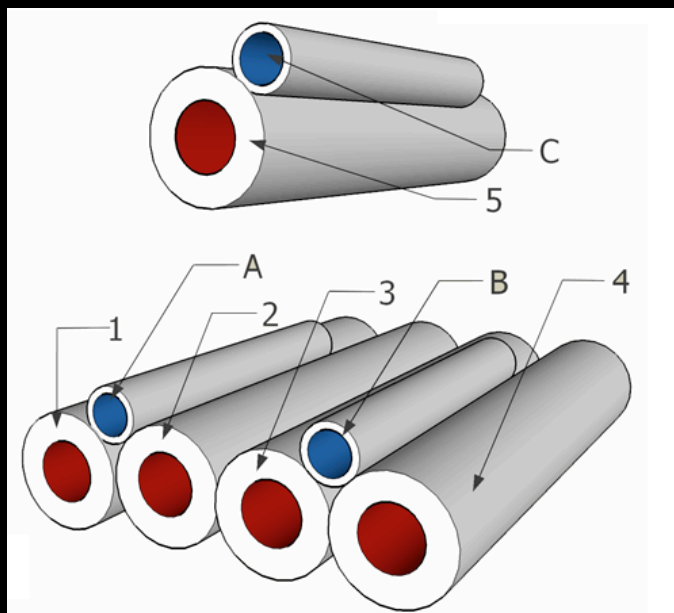
Hands-on experience in the design of sensors for micro mobile robots.



↑ Robot reading a bar code and ↑ scheme of functioning (top view)
composition of a bar code (frontal view) →

Designing your own sensors (6)

Hands-on experience in the design of sensors for micro mobile robots.



Scheme of the procedure for reading a bar code once the fiducial point has been detected.

Designing your own sensors (6)

Hands-on experience in the design of sensors for micro mobile robots.

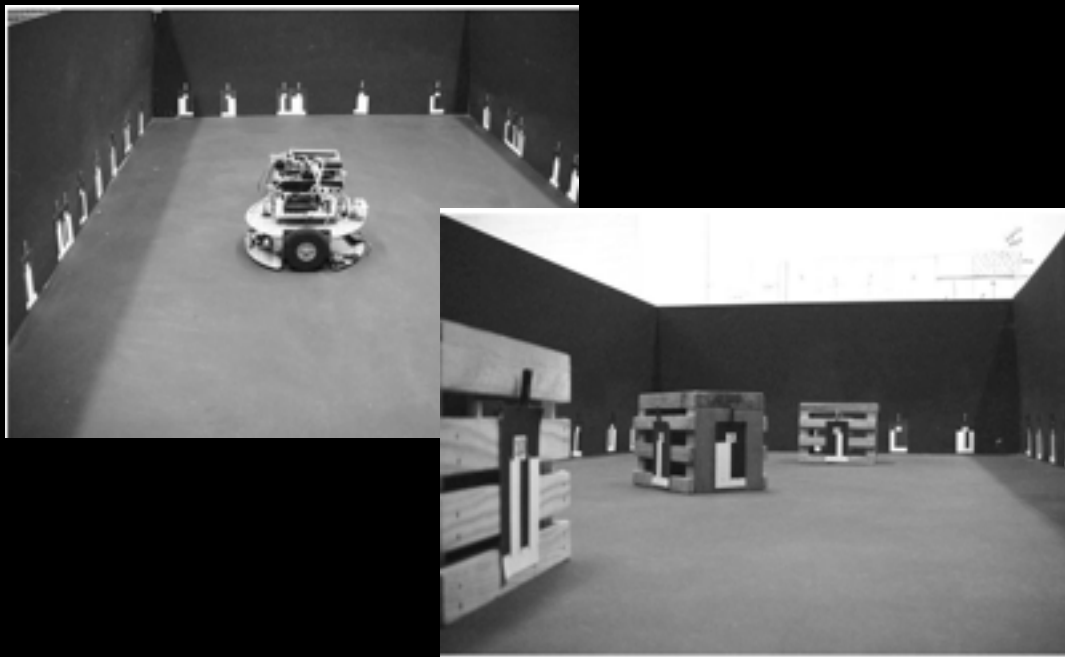


TABLE I

<i>Time (min-secs)</i>	<i>Bar code</i>		<i>Distance (cm)</i>	<i>Angle (degrees)</i>
	<i>actual</i>	<i>read</i>		
3'50"	5	5	32.7	85
8'45"	7	7	24.0	60
13'53"	9	1	14.6	80
15'05"	2	2	25.4	83
17'15"	12	12	12.5	66
18'07"	5	1	13.0	70
18'34"	5	5	13.9	65
29'25"	1	1	11.0	60

TABLE II

<i>Time (min-secs)</i>	<i>Bar code</i>		<i>Distance (cm)</i>	<i>Angle (degrees)</i>
	<i>actual</i>	<i>read</i>		
2'43"	13	11	10.0	50
17'45"	12	12	20.2	89
18'07"	11	11	10.2	63
18'36"	9	9	27.0	89
23'17"	5	5	19.8	85
23'34"	5	1	9.8	62
25'49"	12	12	18.0	77
26'43"	10	10	26.8	66

Robot and environment, and results of recognition when moving at slow (4cm/se) and "fast" (6.33 cm/sec) speed.

Final Remarks

Don't trust blindly your sensor! Read its datasheet and characterize it.

In spite of their accuracy two different sensors can complement each other.

A lot of work has to be done for synthesizing features provided by sensors.

Ad-hoc sensors need a lot of do-it-yourself work.

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Many thanks!

More information

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