MINES Saint-Étienne

Une école de l'IMT

Work Time Analytics in Emergency Departments Using Localization Sensors

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INSPIRING INNOVATION SINCE 1816

Context: real-time data collection

- Indoor Positioning System (IPS) is a **promising technology for on-site diagnostic** of an existing organization, and as a potential evaluation tool for **future reorganizations**
- **Complementary** to the application of quantitative or qualitative evaluation methods (e.g., Shadowing, Process Mining)

In this study, we explore how IPS data could provide a better understanding of the organization and production of emergency care, by objectifying how healthcare professionals allocate their time and transit within the emergency department.

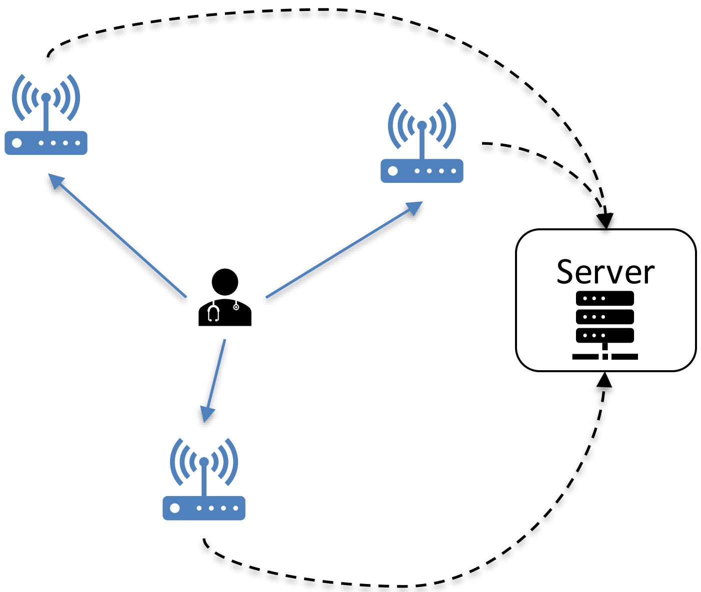
- The technology experimented offers **perspective for future work**, such as the **tracking of objects and patients**, as well as the collection of real-time data to feed a **digital twin**

Context: Indoor positioning systems (IPS)

- **IPS** operates in a similar way to GPS and uses the principle of triangularization to determine the location of an object or person.

- **Signals** from GPS satellites are easily **degraded by buildings**, making this technology inappropriate for indoor environments.

- Instead, IPS based on **radio frequency signals** uses **anchors** placed directly inside the building.



Context: Indoor positioning systems (IPS)

- In the literature, many applications of IPSs for **asset tracking** in hospitals have shown potential for **inventory and commodity management** (Álvarez López et al., 2018; Yoo et al., 2018).

- A few studies have tested the use of IPSs for **object-based activity recognition**, especially in the context of trauma resuscitation, where a list of objects can be defined as related to a given activity (Li et al., 2016; Parlak et al., 2011).

- However, the use of IPS to directly **track the motion of healthcare professionals** in hospitals is still in an **experimental phase**.

Experiment of an IPS in Le Corbusier Hospital (Firminy)

Technology:

- 20 anchors covering the entire emergency department (ED)
- 27 tags (sensors) to track healthcare professionals during their shift
- IPS based on radio-frequencies signals (Ultra-Wide Band)

Study period: March 7th to April 21st 2022

Data collected: timestamped location within the ED, 5 times per second

Participants: assistant nurses, triage nurses, intensive care unit (ICU) nurses, waiting room nurses, short-stay unit (SSU) nurses, managers, doctors and on duty doctors

Map of the ED

Care coordination
Informatics
Transit
Transit / Informatics / Care
Care preparation
Other
Managment
Cleaning and Stock
Stock
Care

Time allocation

Overall, the burden of **non-care-related** activities is largely induced by **administrative duties and transit**.

This is especially relevant for **doctors** and **on-duty doctors**, who spend approximately one-third of their time in **transit** and a quarter of their time on **administrative** duties.

Table 2: Proportion of time spent on care-related activities.

	Care-related activities (% of available time)	
	Lower Bound	Upper Bound
Assistant nurse	26%	57%
Manager	18%	31%
Triage nurse	40%	45%
ICU nurse	45%	53%
Waiting room nurse	34%	66%
SSU nurse	31%	66%
Doctor	26%	39%
On duty doctor	33%	39%

Note: Care-related activities included in the lower bound are care, care coordination and care preparation. In the upper bound, the mixed area of transit informatics and care is also added.

Time allocation

Model: Fractional multinomial Logit

- Dep. var: multiclass proportions
- Indep. var: hourly patient loads

Main result: burden of administrative duties substantially increased along with patient load for doctors and on-duty doctors, by a maximum of 22 pp and 16 pp, respectively.

- On-duty doctors counterbalanced by reducing their time in other activities (no effect on time dedicated to care)
- Doctors reduced their time spent on other activities, as well as in care-related activities

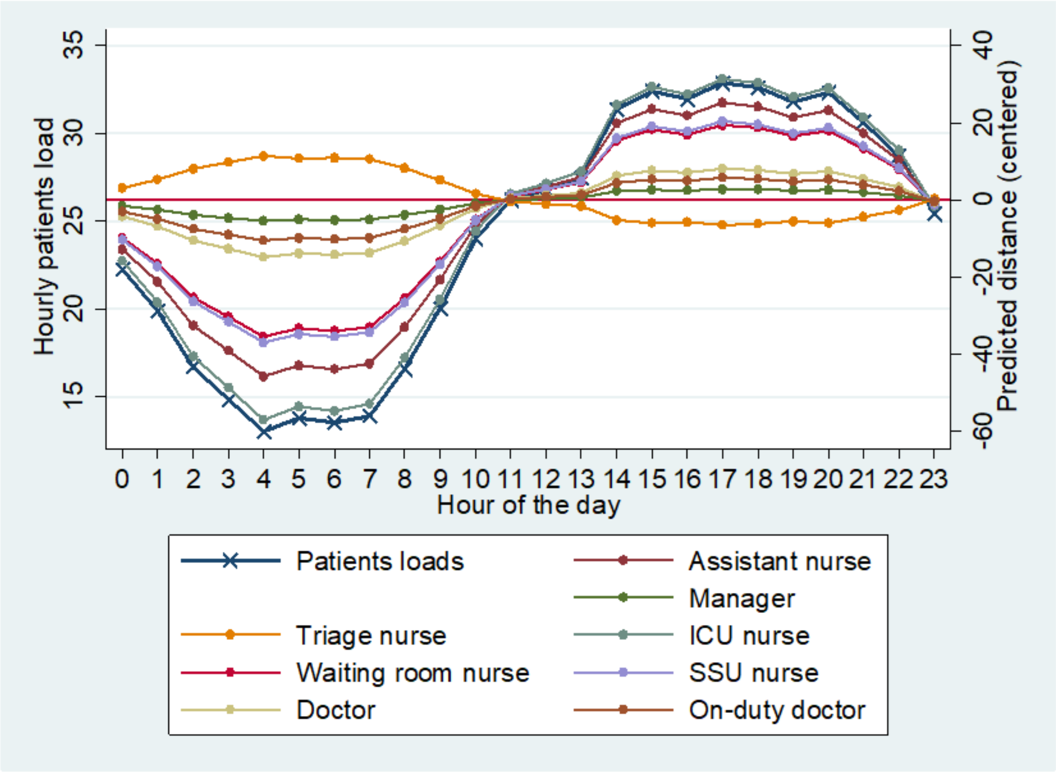
Walking distance

Model: OLS

- Dep. var: hourly walking distance
- Indep. var: hourly patient loads

Main result on the sensitivity of walking distances to patient loads:

- **No effect** for doctors, on-duty doctors, managers and triage nurses
- **Significant effect:** highest predicted distance (i.e., at 5PM) is 23%, 29%, 16%, and 18% higher compared to the lowest one (i.e., at 4AM) respectively for assistant nurses, ICU nurses, waiting room nurses and SSU nurses.



Walking distance

Surface of activity : defined as the surface area of the most frequently visited hexagons, where an individual spent 95% of their time.

Predicted distance / surface : informative about the degree of repeated movement or repeated trips, as it represents the average walking distance per square meter of the surface of activity.

Label	Shift	Cumulated predicted distance (meters)	Surface of activity (95%, in square meter)		Predicted distance / surface
			Mean	Std	
Assistant nurse	8AM – 8PM	4271	254	93.86	17
Triage nurse	8AM – 8PM	3956	176	78.06	22
ICU nurse	8AM – 8PM	4412	218	77.31	21
Waiting room nurse	8AM – 8PM	4565	256	60.78	18
SSU nurse	8AM – 8PM	4386	219	57.62	20
Doctor	8AM – 8PM	1969	77	33.04	25
On-duty doctor	8AM – 8AM	2004	119	40.93	17
Manager	9AM – 6PM	1337	80	39.77	17

Note: Standard deviation (std).

Staff recognition algorithm

We employed a Random Forest Classifier algorithm to predict our multi-class target variable (i.e., the type of healthcare professional) based on the predictive features.

Step 1: Data were grouped into sequences of observations (representing a 12 hours shift).

Step 2: We created a (virtual) hexagonal grid over the entire ED floor plan to discretize the ED into a multitude of sub-areas.

Step 3: For each sequence, we computed the proportion of time spent in each hexagon, which would be used as predictive features.

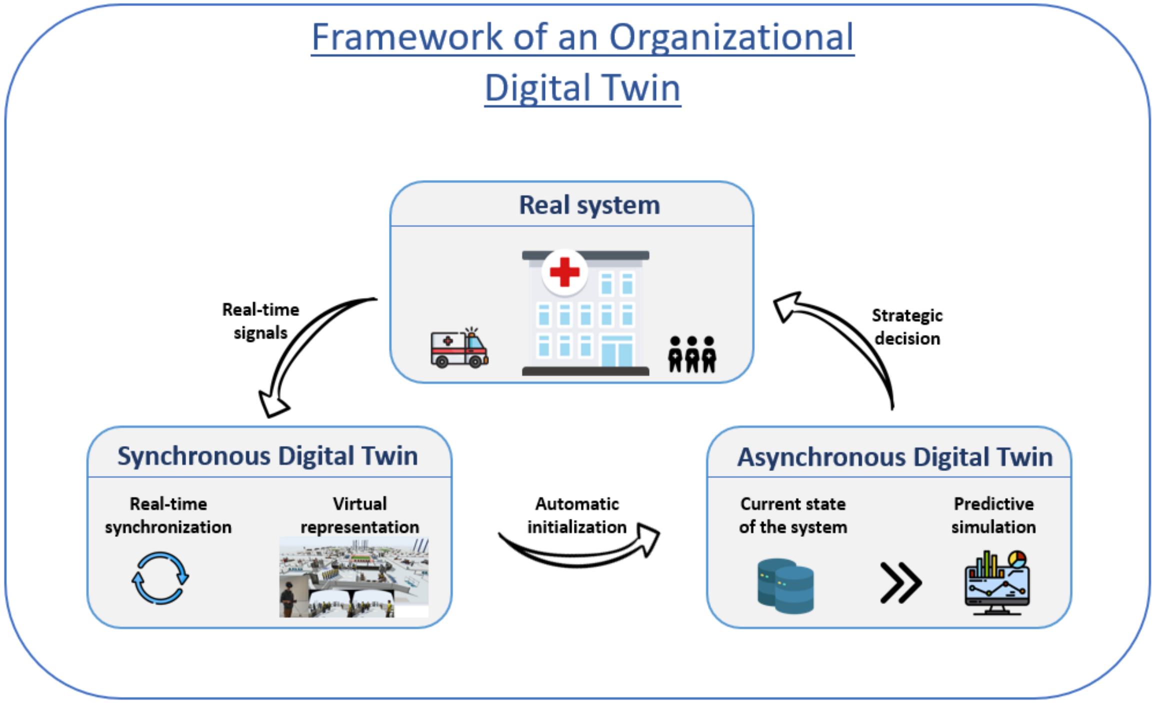
User recognition algorithm

Table A1: Description of the sequences (frequencies).

	Train	Test	Total
- Assistant nurse	70	23	93
- Manager	21	7	28
- Triage nurse	4	1	5
- ICU nurse	22	7	29
- Waiting room nurse	15	5	20
- SSU nurse	19	7	26
- Doctor	48	16	64
- On-duty doctor	37	13	50
Total	236	79	315

	Hexagons' length	Nb features	Features selected	Accuracy
Baseline_100	100	1802	All	86,08%
SelectKBest_100	100	1802	78	92,40%
Baseline_125	125	1213	All	86,08%
SelectKBest_125	125	1213	65	92,40%
Baseline_150	150	882	All	82,28%
SelectKBest_150	150	882	86	91,13%
Baseline_175	175	659	All	91,14%
SelectKBest_175	**175**	**659**	**51**	**96,20%**
Baseline_200	200	523	All	86,08%
SelectKBest_200	200	523	47	93,67%
Baseline_250	250	357	All	82,28%
SelectKBest_250	250	357	54	91,14%
Baseline_300	300	251	All	87,34%
SelectKBest_300	300	251	65	93,67%
Baseline_350	350	189	All	84,81%
SelectKBest_350	350	189	31	94,93%

Perspectives – Digital Twin



Perspectives – Digital Twin

References

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Appendix

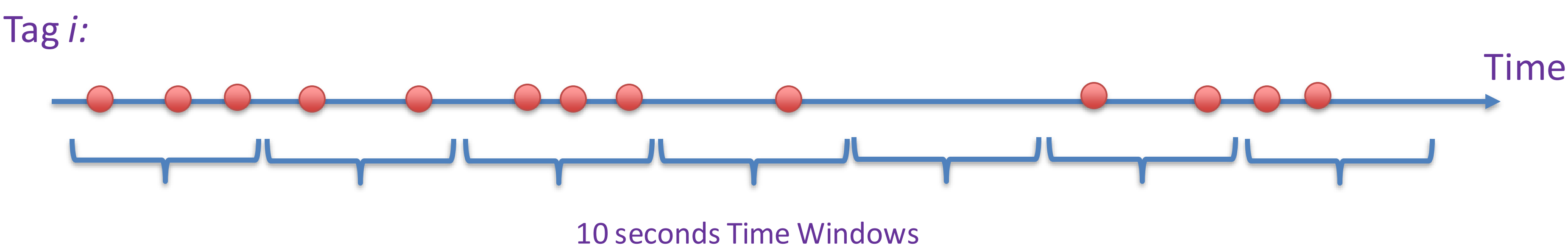
Confusion Matrix of the best classifier (Accuracy=96,2%)

Predicted

		AS	CHEF	IOA	SAU	Tampon	UHCD	MED	M_Garde
Observed	AS	23	0	0	0	0	0	0	0
	CHEF	0	7	0	0	0	0	0	0
	IOA	0	0	0	1	0	0	0	0
	SAU	0	0	0	7	0	0	0	0
	Tampon	0	0	0	0	5	0	0	0
	UHCD	0	0	1	0	0	6	0	0
	MED	0	0	0	0	0	0	15	1
	M_Garde	0	0	0	0	0	0	0	13

Smoothing: 10 seconds time windows Algorithm

- Define 10 seconds time windows
- Attribute most frequent polygon among obs of time window
- Coordinates: compute barycenter / randomly select one obs



# of obs per tag per time window (10sec) : mean=36.86, min=1, max=90

Pooled OLS specification for walking distances

We investigate the correlation between healthcare professionals' hourly walking distance and patient loads through a Pooled Ordinary Least Squares regression.

The full specification of the accumulated walking distance of tag i during hour t can be expressed as:

$$Distance_{i,t} = \alpha + Flow_t + \sum_{l=1}^{l=8} \beta_l \, label_{i,l} + \sum_{l=1}^{l=8} \gamma_l \, (label_{i,l} \, X \, Flow_t) + \epsilon_{i,t}$$

Where α is the intercept, $Flow_t$ refers to the patient load during hour t, $label_{i,l}$ are dummy variables associated with the eight tag labels, and $\epsilon_{i,t}$ is the normally distributed error term. To account for potential correlations among observations of the same tag, standard errors are adjusted for tag clusters, allowing intra-cluster error correlation.

Patient flow