Improving the estimation of fingerprint spatial relationships via deep metric learning on continuous similarities

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I. Introduction and motivation

Among existing approaches to indoor positioning, WiFi fingerprinting is the most common one. Its diffusion is largely due to its ease of deployment: WiFi access points (APs) are, nowadays, ubiquitous and ad-hoc equipment is not required for their exploitation. Moreover, knowing the Received Signal Strength (RSS) from the access points, rather than their exact location, is enough to derive precise position information.

In fingerprinting, a training set of n examples can be defined as a collection of (fingerprint, location) pairs $\mathcal{P} = \{(\mathbf{x}, \mathbf{y})_i \mid 1 \leq i \leq n, \mathbf{x} \in \mathbb{R}^m, \mathbf{y} \in \mathbb{R}^p\}$, where m is the number of available APs and p is the number of dimensions used to represent the locations (e.g., $p = 3$ in a 3D-based modeling). Each vector in $\mathbb{R}^m$ contains the RSSs of all the APs that are visible at the specific location. We can define the localization task as a (learnable) function $l_\theta : \mathbb{R}^m \to \mathbb{R}^p$. The goal is to find the parameters θ that allow to obtain the best possible modeling of the problem, also generalizable to newly observed fingerprints.

Deterministic algorithms are the most classical solution to perform fingerprint-based positioning. Such approaches include (k-)Nearest Neighbour, in which a newly observed fingerprint is compared against those already collected, retrieving the k most similar ones according to a metric. Then, the position estimate for the candidate fingerprint is determined as the (weighted) centroid of the coordinates of such instances. In the literature, the performance of classical metrics has been studied in several works (e.g., [1]), showing that their choice is a fundamental task for the development of an effective positioning solution. However, only recently the focus has turned to investigating the degree to which classical metrics (working in $\mathbb{R}^m$) capture the spatial relationships (in $\mathbb{R}^p$) among the locations associated with the fingerprints. In [2], authors showed that some metrics clearly outperform others, but none is capable to mimic the relationships in $\mathbb{R}^p$. A following study that relied on a meta-metric learnt via symbolic regression was able to produce only a small improvement in such regard, suggesting that methods capable of learning *richer representations* should be taken into account.

Notably, being able to estimate the spatial relationships among fingerprints by working directly in $\mathbb{R}^m$ would be of great importance within indoor positioning tasks. For example, it could largely reduce the effort required for the fingerprints collection and labeling phases, promote crowdsourced-based strategies, and foster the development of semi-supervised approaches.

II. The proposed approach

Richer representations could be obtained by means of deep metric learning, which aims to learn similarity metrics in an end-to-end fashion with deep neural networks. In principle, such a technique can be employed to capture any kind of semantic similarity between labels. However, most of the literature has been focusing on computer vision and binary labels over pairs of elements, simply assessing whether they are similar or not [3]. The main reason is that, if continuous labels are instead considered, the semantics associated to their similarities is far richer. In such a scenario, when comparing elements in the latent space, a good approach should *(i)* preserve their relative ordering, and *(ii)* produce distance values that resemble some properties observed among distances computed in the label space.

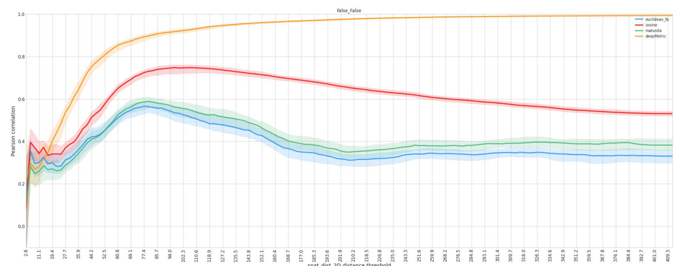

Fig. 1. Pearson correlation between spatial and latent distances at multiple spatial distance thresholds.

In the fingerprinting case, we are interested in obtaining distances in the latent space that are proportional to those calculated among the labels, i.e., on the real-world locations. A possible solution to achieve this is to rely on distance ratios, requiring that:

$$\frac{s(\mathbf{y}_i, \mathbf{y}_j)}{s(\mathbf{y}_k, \mathbf{y}_h)} = c \cdot \frac{\| \phi_\theta(\mathbf{x}_i) - \phi_\theta(\mathbf{x}_j) \|_2^2}{\| \phi_\theta(\mathbf{x}_k) - \phi_\theta(\mathbf{x}_h) \|_2^2},$$

where $s : \mathbb{R}^p \times \mathbb{R}^p \to \mathbb{R}$ is a function that calculates the distance between pairs of elements i, j by looking at their labels $\mathbf{y}_i$ and $\mathbf{y}_j$ (e.g., for fingerprinting, the Euclidean distance), ϕ_θ is a parameterized neural network $\phi_\theta : \mathbb{R}^m \to \mathbb{R}^z$ (where $\mathbb{R}^z$ is the latent space), and c is a scaling factor.

III. Preliminary results and open issues

We applied our approach to a large fingerprint dataset evaluating its capability to preserve spatial relationship compared to a selection of classical metrics. Preliminary results (see Figure 1) are very encouraging, however, performances drop when dealing with fingerprints that are spatially very close. The causes of this phenomenon are probably diverse and currently under investigation. Possible explanations include: an uneven distribution of training samples used to train the deep learning model; and, an inherent difficulty capturing distance relationships among fingerprints that are very close, thus proportionally more affected by signal perturbations.

References

[1] J. Torres-Sospedra *et al.*, "Comprehensive analysis of distance and similarity measures for wi-fi fingerprinting indoor positioning systems," *Expert Systems with Applications*, 2015.

[2] N. Saccomanno *et al.*, "What you sense is not where you are: On the relationships between fingerprints and spatial knowledge in indoor positioning," *IEEE Sensors Journal*, 2021.

[3] S. Kim *et al.*, "Deep metric learning beyond binary supervision," in *Proceedings of the IEEE/CVF CVPR*, 2019.