A ROUTE IDENTIFICATION ALGORITHM FOR ASSISTED LIVING APPLICATIONS FUSING WLAN, GPS AND IMAGE MATCHING DATA

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1. INTRODUCTION

This paper addresses the automatic identification of often-traversed routes for assisted living applications using WLAN technology in addition to other modalities. This problem is complicated by a number of factors, including the changing and noisy nature of the WLAN channel, the need to track users seamlessly in both indoor and outdoor environments, the need for robustness to slight deviations in the precise path taken, and speed, along a route. In this work commonly traversed routes are identified by clustering based on sensed data, two of which take the form of wireless signals: GPS and WLAN. The latter is particularly important as it can be used both indoors and outdoors. In addition an efficient image matching algorithm is implemented to process data from images automatically taken along the route. In this work a finite number of routes were identified within the DCU campus. Each route was traversed many times over a period of 6 weeks and data sequences collected automatically on each occasion. Each such traversal of a route is referred to as a *trip* in what follows. Section (2) outlines the use of Multidimensional Time Warping in order to automatically cluster trips corresponding to specific routes based on wireless and image data sensed on each trip. Section (3) outlines the manner in which data was sensed and presents clustering results for each modality individually as well as results based on a fusion of the data.

2. MULTIDIMENSIONAL DYNAMIC TIME WARPING

In order to find a similarity measure for data collected during different trips the Multidimensional Dynamic Time Warping Algorithm [1] was employed. The classic DTW algorithm uses a local distance measure to determine the distance between a class sequence and a test sequence by calculating a warping path on the DTW distance table. Suppose there are two sequences of data i.e. a class sequence C of length I and test sequence T of length J. To measure the similarity between these two sequences, an $I \times J$ distance-table D is constructed, where $d(i,j)$ is the local distance between C_i, the i^{th} element of C and T_j, the j^{th} element of T. Warping paths W are then calculated from the distance table, each of which consists of a set of distance-table elements that define a mapping and alignment between C and T:

$$W = \left\{ w(i(q), j(q)) \,\middle|\, \begin{array}{l} q = 1, ..., Q, \\ \max(I,J) \leq Q \leq I + J - 1 \end{array} \right\} \quad (1)$$

The overall distance associated with each warping path W is obtained by summing the local distances $d(i,j)$ along it. One popular choice for finding the best alignment between the class sequence and the test sequence is to identify the warping path that minimises this overall distance. This minimal distance is therefore a measure of the similarity between the data sequences. In the experiments described below each data sequence was multidimensional, (for example the WLAN measurements record signal strength from 3 separate MAC addresses, while GPS data sequences record both longitude and latitude) and the DTW algorithm must be correspondingly generalised. In order to switch to higher dimensions the class template $C(I \times V)$ and test template $T(J \times V)$ are used. They represent multimodal sequences where V is the number of variables. To calculate the DTW distance between the test and class templates, the extended *Euclidean distance* is used as the local distance measure to calculate the difference between the two vectors of length V, C_i^V and T_j^V. It is defined as :

$$d_E(C_i^V, T_j^V) = \sqrt{\sum_{v=1}^{V} WV(v)(C_{i,v} - T_{j,v})^2} \quad (2)$$

where WV is a positive definite weight vector. The weight vector WV can be used in the MDTW algorithm to give more weight to certain variables to improve the performance of recognition but since all the variables in our data are of equal importance we set WV equal to 1 in what follows.

3. EXPERIMENTAL SET-UP AND RESULTS

A set of training data was collected simultaneously using a SenseCam GiSTEQ GPS device and Campaignr software (for collecting signal strengths data) installed on a N95 Nokia cellphone. Measurements were taken on 6 selected routes within and around the DCU campus. The devices were synchronized and the data recording was collected at regular time intervals (every 1, 15 and 30 seconds for GPS, SenseCam and Campaignr respectively). Each route was traversed 5 times (i.e. 5 trips) over a period of 6 weeks, yielding 30 sets of data overall. Signal strength information is considered to be 3-dimensional (V in section (2) equals 3) as the same 3 MAC addresses were discernible along each trip. GPS data is deemed to be 2-dimensional (consisting of longitude and latitude coordinates at each point). Two data-matrices of order $N \times 3$ and $M \times 2$ were thus collected corresponding to WLAN and GPS data for each of the 30 trips, where N and M depended on the length of time the trip took. The MDTW was then applied to each pair of data sequences for each modality. In the case of image data the MDTW algorithm was applied to every two sets of images taken by the SenseCam. The elements of the local distance matrix in this case corresponded to the number of features matched between images in each set (multiplied by -1 in order that the minimal path would correspond to the path with most matches). The matching features were identified using the SURF algorithm [2]. A greater weight was placed on bi-directional matches indicating the greater level of confidence ascribed to them. For each of the three modalities a 30×30 distance matrix representing the level of similarity between each pair of trips was thus produced by the MTDW algorithm. A fourth matrix was formed as an equally weighted linear combination of the previous three normalized distance matrices. The distance matrices were then processed (using 170 iterations of the clustering algorithm described on page 368 of [3]) to form figures 1-4 , which are a spatial representation of where each trip resides in the appropriate signal-space. It is noted that similar trips along the same route tend to cluster together and can be identified as such (these are explicitly grouped in figure 4). The fusion algorithm was able to successfully identify each of the 6 routes, something not managed by any of the 3 modalities when applied individually. Future work will further investigate the accuracy and robustness of the methods presented as well as the choice of weights in the MDTW and fusion algorithms.

4. ACKNOWLEDGEMENTS

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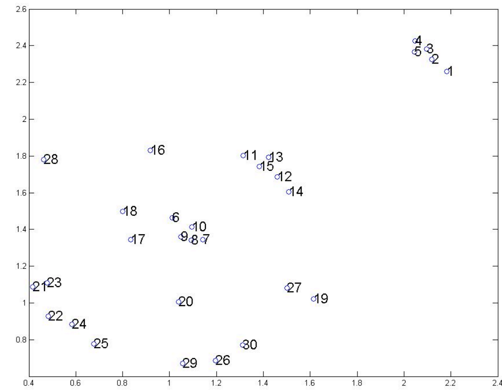

Fig. 1. Clustering of trips based on GPS data

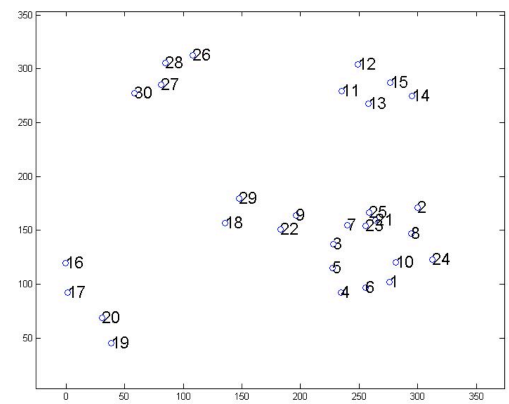

Fig. 2. Clustering of trips based on WLAN data

5. REFERENCES

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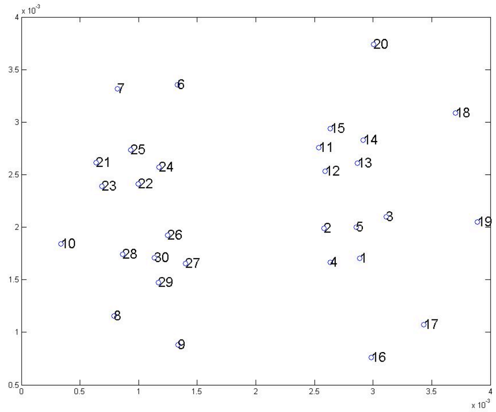

Fig. 3. Clustering of trips based on image matching

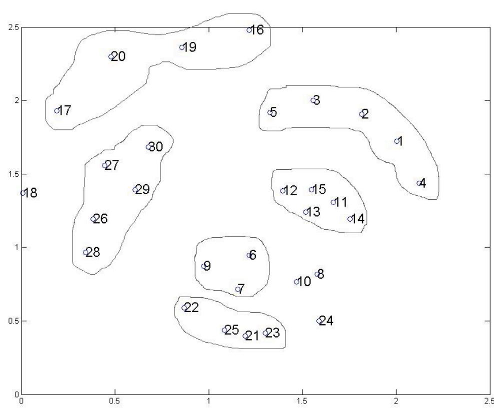

Fig. 4. Clustering of trips based on fused data