Activity Recognition Based on a Multi-sensor Meta-classifier

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Abstract. Ensuring ubiquity, robustness and continuity of monitoring is of key importance in activity recognition. To that end, multiple sensor configurations and fusion techniques are ever more used. In this paper we present a multi-sensor meta-classifier that aggregates the knowledge of several sensor-based decision entities to provide a unique and reliable activity classification. This model introduces a new weighting scheme which improves the rating of the impact that each entity has on the decision fusion process. Sensitivity and specificity are particularly considered as insertion and rejection weighting metrics instead of the overall accuracy classification performance proposed in a previous work. For the sake of comparison, both new and previous weighting models together with feature fusion models are tested on an extensive activity recognition benchmark dataset. The results demonstrate that the new weighting scheme enhances the decision aggregation thus leading to an improved recognition system.

Keywords: Meta-classifier, Sensor network, Decision fusion, Weighted decision, Aggregation, Activity recognition, Human Behavior.

1 Introduction

The assessment of human behavior has been demonstrated of worth value for its several applications in healthcare [3], rehabilitation [1], industrial maintenance [16] or gaming [11] among others. Even when relevant contributions have been provided in the last years to the activity recognition field, there are still several open issues respectively referring to systems reliability, robustness, pervasiveness and seamless of usage. The use of multiple sensor configurations appears in this context as a means to effiently overcome some of these issues.

In wearable computing, several studies have already demonstrated the importance of monitoring different body parts to increase activity detection capabilities [7,15]. To do so, more than one sensor is normally required to be attached

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at various body locations. However, obtrusiveness has traditionally been one of the main controversial drawbacks against the wearing of multiple sensors, since their size and ergonomic limitations may difficult their use in life-long conditions. Nonetheless, progressive sensors miniaturization and cost reductions are supporting a new generation of devices that may be embedded in garments and textiles [2], with the aim of integrating tens, hundreds or even thousands of these sensors in a very reduced area [8].

Together with this mainstream technologies, sensor fusion has become a hot topic in activity recognition. Sensor fusion applies to different levels of the activity recognition chain, including signal fusion, feature fusion and classification decision fusion. Thus for example, [13] combines features extracted from different signal domains (respiration and acceleration) to recognize a set of 13 types of activities of varying intensities; [18] uses the fusion of 3D acceleration and angular velocity signals for spotting up to eight regular daily activities; the relationship between activity intensity and physiological response is also leveraged in [14] through correlating motion with heart rate or skin temperature data, which improves the accuracy of activity detection. At a higher level [12] fuses the classification scores provided by support vector machines (SVM) and gaussian mixture models (GMM) that operate on acceleration and electrocardiogram data. In [10] the fusion concept is also incorporated in a more sophisticated hierarchical model that combines information from dynamically-selected acceleration sensor nodes.

In this work we present a multi-sensor meta-classifier that incorporates an improved version of the weighting scheme introduced in a previous work [4]. This improvement allow us to independently weight the positive (insertion) and negative (rejection) decisions yielded by each decision making entity, instead of using the same value for both. This way is more problem-sensitive and supports the use of potential decision entities even when their classification or rejection capabilities are unbalanced. The rest of the paper is organized as follows. In Section 2 the meta-classifier structure and the decision weighting scheme are described. Section 3 presents the main results obtained for the meta-classifier when tested on an activity recognition benchmark dataset. The proposed model is also compared with a previous hierarchical version and a standard feature fusion model. Finally, main conclusions and future steps are presented in Section 4.

2 Multi-sensor Meta-classifier

Meta-classification is a prominent subfield of machine learning which shares conceptual basis with other state-of-the-art meta-algorithms such as stacking, boosting or mixture of experts among others. In this paper we refer to this as those models based on the aggregation of the decision provided by several sources or nodes of information. In the model presented here the decisions are provided by different level classification entities (hierarchical classification). Moreover, each decision is particularly rated according to each entity classification capabilities (e.g., from the sensor informativeness). This weighting procedure supports an optimal exploitation of the classification potential of each individual entity, thus allowing for the definition of a precise collective knowledge structure.

The structure of the meta-classifier is very similar to the one presented in [4]. This consists of three classification levels or stages. The first level is composed by a set of M by N binary or base classifiers (c_{mn}, $\forall m = 1, \ldots, M, n = 1, \ldots, N$) which respectively specialize in the discrimination of the activity or class n by using the information from the sensor or node m. The second classification level is defined through M node or source classifiers (S_m, $\forall m = 1, \ldots, M$) which defines through the decision fusion of each sensor associated binary classifiers. On top of the model (third level) the fusion of the decisions given by the source classifiers provides the eventually yielded activity classification.

The model training requires from just a few steps. Firstly, the training dataset is partitioned in three equally-distributed parts. One of these partitions is used to train the base classifier entities. Afterwards, another partition is used to test the performance of the binary classifiers. From here, statistical metrics are obtained and later used to define the first level of weighting parameters. Once the models are trained and the metrics obtained the source classifiers are almost defined. Then, the weighting parameters for the second level are assessed. To that end, the third yet unused part of the dataset is considered now for the evaluation of the source classifiers performance. From the test statistics the second level weights may be obtained. At this point the source classifiers are completely defined. The meta-classifier is by extension defined as the sources classifiers and weights are, thus completing the final stage of the model. The final structure may be seen in Figure 1.

In the following the computation of the first level and second level weights as well as the suggested decision fusion scheme are presented. As was already introduced, two parameters are used both to weight classifications/insertions and rejections. At the class level these parameters are defined as α_{mn} and β_{mn} which respectively represent the insertion and rejection weights for c_{mn}. The values of α_{mn} and β_{mn} are obtained from the performance assessment of c_{mn}. In particular, α_{mn} corresponds to the sensitivity whilst β_{mn} to the computed specificity. We have selected these performance parameters since they represent well the insertion and rejection capabilities of the classifier. From the statistical theory, given TP_{mn} (true positives) the number of correctly identified samples, FP_{mn} (false positives) the incorrectly identified samples, TN_{mn} (true negatives) the number of correctly rejected samples and FN_{mn} (false negatives) the incorrectly rejected samples, all specifically for the classifier c_{mn}, α_{mn} and β_{mn} may be defined as:

$$\alpha_{mn} = \frac{TP_{mn}}{TP_{mn} + FN_{mn}} \tag{1}$$

$$\beta_{mn} = \frac{TN_{mn}}{TN_{mn} + FP_{mn}} \tag{2}$$

These weights represent the importance that each base classifier will have on the source classifier decision scheme. A specific voting algorithm is considered

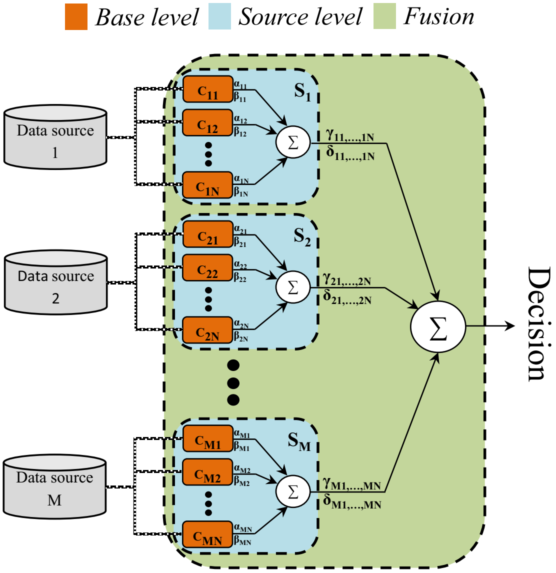

Fig. 1. Meta-classifier scheme. α_{mn} and β_{mn}, and γ_m and δ_m correspond to the insertion/rejection weights for the base level and source level respectively.

at this stage to fuse the base classifier individual decisions on a unique decision for each source respectively. For a source m, given a sample x_{m_k} to be classified and being q the class predicted by the classifier c_{mn}, if such class belongs to the class of specialization ($q = n$), the classifier will set its decision to α_{mn} for the class n and 0 for the rest of the classes. Otherwise ($q \neq n$), the decision is set to 0 for the class n and β_{mn} for the others. In summary, the classifier c_{mn} weighted decision (WD_{mn}) for the class q may be defined as ($\forall \{q, n\} = 1, \ldots, N$):

$$WD_{mn}\left(x_{m_k}\right) = \begin{cases} \alpha_{mn}, & x_{m_k} \text{ classified as } q \\ 0, & x_{m_k} \text{ not classified as } q \end{cases} \quad (\forall q = n) \\ \begin{cases} \beta_{mn}, & x_{m_k} \text{ not classified as } q \\ 0, & x_{m_k} \text{ classified as } q \end{cases} \quad (\forall q \neq n) \tag{3}$$

The aggregation of the weighted decisions provided by each base classifier for the *m-th* source classifier (S_m) may be computed as follows:

$$O_m\left(x_{m_k}\right) = \sum_{n=1}^{N} WD_{mn}\left(x_{m_k}\right) \tag{4}$$

The class predicted by S_m is the class q for which the source classifier output is maximized:

$$q_m\left(x_{m_k}\right) = \underset{q}{\operatorname{argmax}}\left(O_m\left(x_{m_k}\right)\right) \tag{5}$$

For the next level, similar parameters to α_{mn} and β_{mn} are considered, here defined as γ_m (insertions) and δ_m (rejections). Nonetheless, the way they are computed varies slightly with respect to the above described. At the source level the classifiers are not binary but multiclass models. Therefore, the evaluation of each source classifier requires to extend sensitivity and specificity concepts to the multiclass case (see details in [17]). According to this generalization, γ_m and δ_m may be described as:

$$\gamma_m = \langle \gamma_{m1}, \gamma_{m2}, \ldots, \gamma_{mn} \rangle = \left\langle \frac{TP_{m1}}{TP_{m1} + FN_{m1}}, \frac{TP_{m2}}{TP_{m1} + FN_{m2}}, \ldots, \frac{TP_{mn}}{TP_{mn} + FN_{mn}} \right\rangle \tag{6}$$

$$\delta_m = \langle \delta_{m1}, \delta_{m2}, \ldots, \delta_{mn} \rangle = \left\langle \frac{TN_{m1}}{TN_{m1} + FP_{m1}}, \frac{TN_{m2}}{TN_{m1} + FP_{m2}}, \ldots, \frac{TN_{mn}}{TN_{mn} + FP_{mn}} \right\rangle \tag{7}$$

where $\{TP/TN/FP/FN\}_{mn}$ refer to the previous described classification and rejection counting values, but now computed for each class k across the confusion matrix results obtained from the evaluation of S_m ($\forall m = 1, \ldots, M, n = 1, \ldots, N$). The source level weights are used in a different manner than in the class level. Besides the decisions are now made in a multiclass way, the weights are used to reward or penalize those classes that are classified or not by each source classifier. Accordingly, given q_m the decision of S_m for the sample x_{m_k}, the set of weighted decisions from this classifier is defined as:

$$WD_m\left(q_m\left(x_{m_k}\right)\right) = \begin{cases} \gamma_{mn}, & n = q_m\left(x_{m_k}\right) \\ -\delta_{mn}, & n \neq q_m\left(x_{m_k}\right) \end{cases} \quad (\forall n = 1, \ldots, N) \tag{8}$$

Now, for a sample x_k defined through the corresponding samples delivered by each source $(x_{1_k}, \ldots, x_{m_k})$, the aggregation of the source level weighted decisions is calculated as follows:

$$O\left(x_k\right) = O\left(\{x_{1_k}, \ldots, x_{M_k}\}\right) = \sum_{p=1}^{M} WD_p\left(q_p\left(x_{p_k}\right)\right) \tag{9}$$

Finally, and similarly to (5), the eventually yielded class q is obtained as:

$$q = \underset{q}{\operatorname{argmax}}\left(O\left(x_k\right)\right) \tag{10}$$

3 Results and Discussion

For the evaluation of the proposed model an activity recognition benchmark dataset is used [6]. This dataset comprises motion data (namely acceleration, rate of turn and magnetic field) recorded for 17 volunteers performing 33 fitness activities while wearing a set of nine inertial sensors attached to different parts of their bodies. For the sake of simplicity, the 3D acceleration data from the so-defined "ideal-placement" recordings are here considered. Three feature sets (FS) are respectively extracted for evaluation: FS1='mean', FS2='mean and standard deviation' and FS3='mean, standard deviation, maximum, minimum and mean crossing rate'. All features are computed over a non-overlapping sliding window (6 seconds size). C4.5 decision trees (DT, [9]), which have been extensively and successfully applied in previous activity recognition problems, are used both for the multiclass classifiers and the binary or base classifiers. For all models a ten-fold random-partitioning cross validation process is applied across all subjects and activities. The process is repeated 100 times for each method to ensure statistical robustness.

In Figure 2 the results for the feature fusion (feature vector composed by the feature extracted from all sensors), hierarchical weighted classifier (HWC, [4]) and the here proposed meta-classifier are shown. FS1, FS2 and FS3 are respectively evaluated on these models for three activity recognition problems of increasing complexity (10 activities, 20 activities and 33 -all- activities). The meta-classifier clearly outperforms in all cases the recognition capabilities of the HWC, which appears to be the less reliable of the tested models. For some cases the accuracy improvement is of up to 13% as for the experiment with 33 activities and FS3. This systematic enhancement demonstrates that the rating

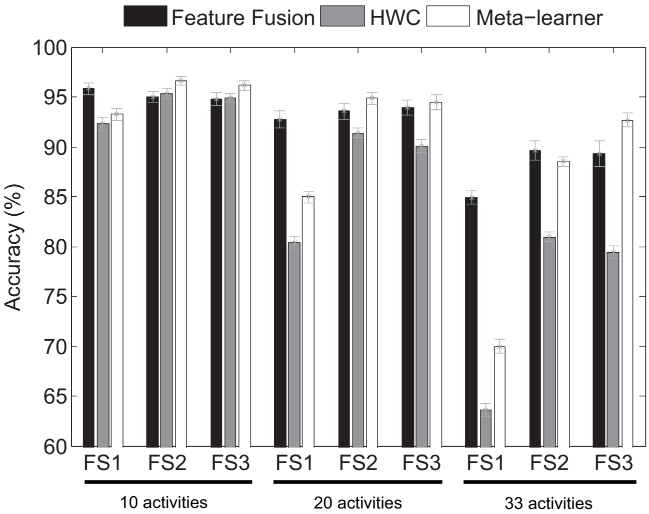

Fig. 2. Accuracy results from the evaluation of the fusion models when tested on different complexity activity recognition datasets. FSi refers to the feature set extracted from the raw acceleration data. The 10 activities dataset refers to the activities $\{1, 2, 18, 20, 23, 25, 30, 31, 32\}$, the 20 activities to $\{1, 2, 3, 7, 12, 13, 17, 18, 19, 20, 21, 23, 25, 27, 28, 29, 30, 31, 32, 33\}$ while the 33 activities dataset comprises all (see [6] for indices equivalence).

of not just the insertions (HWC) but also the rejections translates into a more precise weighting of the decisions yielded by each classifier. Moreover, specificity and sensitivity also contribute to a more balanced description of the classification capabilities than for the use of the overall accuracy.

The differences between the meta-classifier and the feature fusion model are not very significant. Nevertheless, the feature fusion model demonstrates a more regular performance for all problems and feature sets, whereas the meta-classifier shows a significant performance worsening for the 20 and 33 activities problems when FS1 is used. Normally, the more complex (#activities) the problem is the more features are required. Therefore, these reduced recognition capabilities are associated to the limited discrimination potential of the binary classifiers when just a feature (FS1) is considered. Nevertheless, this is shown to be compensated when a richer feature vector is used. In either case, it must be borne in mind that one of the main drawbacks of the feature fusion models is the drop on their activity assessment capabilities during realistic daily-living conditions [5]. A simple anomaly on one of the sensors may potentially affect the whole fusion process and lead to misclassifications. The proposed meta-classifier could deal with this and similar issues since the sources or sensors are independently evaluated and the fusion applies only to the individual yielded decisions.

4 Conclusions and Future Work

In this paper we have presented a meta-classifier scheme for multi-sensor activity recognition that may nevertheless be applied to other multi-source classification problems. The model improves the classification performance of a previous hierarchical fusion version through the weighting of both insertions and rejections at base (activity) and source (sensor) levels. The meta-classifier demonstrates to be sensitive to weak base classifiers, which translates into a significant drop on the recognition capabilities as the number of activities (complexity) increases. Nevertheless, the use of richer feature sets significantly increases the recognition potential. Next steps will aim to compare the robustness capabilities of the proposed meta-classifier against feature fusion models when dealing with complex activity recognition issues such as concept drift and diverse sensor anomalies.

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