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Human Activity Prediction Using Temporal Sequence Pattern Mining

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Abstract— **Data mining is a process of identifying valid information from the large databases. There are many different tasks in data mining such as classification, clustering, prediction, time series analysis, sequence pattern mining, etc. Activity recognition aims to identify the actions and goals of one or more agents from a series of observations on the agent's actions and the environmental conditions. The activity recognition, having considerably matured, so has the number of challenges in designing, implementing, and evaluating activity recognition systems in exiting methodologies. The proposed research focuses on activity recognition using sensors dataset. The proposed research challenges that Human Activity Recognition shares with general pattern recognition and identify those challenges that are specific to Human Activity Recognition. The Human Activity Recognition (HAR) refers to the task of measuring the physical activity of a person via the use of objective technology. This task is extremely challenging owing to the complexity and diversity of humans. The concept of an activity recognition chain as a general-purpose framework for designing and evaluating activity recognition systems. The proposed research comprises components for data acquisition and preprocessing, data segmentation, feature extraction and selection, training and classification, decision fusion, and performance evaluation. The proposed research concludes with the sensor data example problem of recognizing different hand gestures from inertial sensors attached to the upper and lower arm. The proposed research can be implemented for this specific activity recognition problem and demonstrate how different implementations compare and how they impact overall recognition performance.**

Index Terms— **HAR, Data Mining, Decision Fusion**

I. INTRODUCTION

Sequential Pattern Mining is the method of finding interesting sequential patterns among the large databases. It also finds out frequent subsequences as patterns from a sequence database. Enormous amounts of data are continuously being collected and stored in many industries and they are showing interests in mining sequential patterns from their database. Sequential pattern mining has broad applications including web-log analysis, client purchase behavior analysis and medical record analysis. The term "data mining" is primarily used by statisticians, database researchers, and the Management Information System (MIS) and business communities. The term Knowledge Discovery in Databases (KDD) [3] is generally used to refer to the overall process of discovering useful knowledge from data, where data mining is a particular step in this process. The additional steps in the KDD process, such as data preparation, data selection, data cleaning, and proper interpretation of the results of the data mining process, ensure that useful knowledge is derived from the data.

Data mining is an extension of traditional data analysis and statistical approaches in that it incorporates analytical techniques drawn from a range of disciplines including, but not limited to,

- Numerical Analysis.
- Pattern matching and areas of artificial intelligence such as machine learning,
- Neural networks and genetic algorithms.

While many data mining tasks follow a traditional, hypothesis-driven data analysis approach, it is common place to employ an opportunistic, data driven approach that encourages the pattern detection algorithms to find useful trends, patterns, and relationships. Essentially, the two types of data mining approaches differ in whether they seek to build models or to find patterns. The first approach, concerned with building models is, apart from the problems inherent from the large sizes of the data sets, similar to conventional exploratory statistical methods. The objective is to produce an overall summary of a set of data to identify and describe the main features of the shape of the distribution. Examples of such models include a cluster analysis partition of a set of data, a regression model for prediction, and a tree-based classification rule. In model building, a distinction is sometimes made between empirical and mechanistic models. The former (also sometimes called operational) seeks to model relationships without basing them on any underlying theory. The latter (sometimes called substantive or phenomenological) are based on some theory or mechanism for the underlying data generating process. Data mining, almost by definition, is primarily concerned with the operational. The second type of data mining approach, pattern detection, seeks to identify small (but nonetheless possibly important) departures from the norm, to detect unusual patterns of behavior. Examples include unusual spending patterns in credit card usage (for fraud detection), sporadic waveforms in Electro Encephalo Gram (EEG) traces, and objects with patterns of characteristics unlike others. It is this class of strategies that led to the notion of data mining as seeking “nuggets” of information among the mass of data. In general, business databases pose a unique problem for pattern extraction because of their complexity. Furthermore, you will have already addressed many of the problems of data consolidation and put in place maintenance procedures [3]. Thus far, the main industries where data mining is expected to add value to customers are in five industry applications. These include retail, banking, insurance, health care, transportation, and medicine. In each of these [13], there are specific factors in which data mining can prove a valuable asset.

The goal of the activity recognition [14] is an automated analysis (or interpretation) of ongoing events and their context from video data. Human activity recognition and discuss methodologies designed for recognition of activities of individual persons. Approaches utilizing space-time volumes and/or video sequence models are also covered. Next, hierarchical recognition methodologies for high-level activities are presented and compared. We categorize human activities into human actions, human-human interactions, human-object interactions, and group activities, discussing approaches designed for their recognition. Hierarchical state-based approaches and syntactic approaches that interpret videos in terms of stochastic strings are covered. Finally, we discuss description-based approaches that analyze videos by maintaining their knowledge on activities temporal [2], spatial, and logical structures. Recent video datasets designed to encourage human activity recognition research will be discussed as well. This will provide the impetus for future research and applications in more productive areas. Data from the sensors are collected and analyzed using data mining or machine learning algorithms to build activity models and perform activity recognition. In this case, they're recognized activities included human physical movements: walking, running,

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sitting down/up as in. Most of wearable sensors are not very suitable for real applications due to their size or battery life. In sensor-based approach, can use either wearable sensors or object-attached sensors. The most used machine learning is the Hidden Markov Model (HMM) – a graphical oriented method to characterize real world observations in terms of state models. Another good alternative is the Conditional Random Field (CRF) model, which is an un-directed graphical method which allows the dependencies between observations and the use of incomplete information about the probability distribution of a certain observable.

II. Literature Review

In recent years, research shows that modeling temporal structure is a basic methodology for recognition of complex human activity [20]. Early detection aims to recognize an ongoing tiny action from observation of its early stage. For example, an action of "Wishing" can be identified by just observing "Outstretched hand". However, for activity prediction, it aims to infer the intention or an advanced level activity class with observation of only a few action units. The problem defined here is for complex activity which involves various Structural details by temporal logical patterns. The goal of activity prediction is to recognize unfinished single actions from observation of its early stage. Two extensions of Information retrieval paradigm, (i) dynamic and (ii) integral retrieval are proposed to handle the sequential nature of human activities [5]. Then a structure Support Vector Machines (SVM) [8] based event detector is learned to recognize partially observed sequences.

Analysis of complex human activities occurring in videos can be defined in terms of temporal configurations of primitive actions. Prior work typically hand-picks the primitives, their total number, and temporal relations (e.g., allow only followed-by), and then only estimates their relative significance for activity recognition. W. Brendel et al's prior work is by learning what activity parts and their spatiotemporal relations should be captured to represent the activity, and how relevant they are for enabling efficient inference in realistic videos. W. Brendel et al represent videos by spatiotemporal graphs, where nodes correspond to multistage video segments, and edges capture their hierarchical, temporal, and spatial relationships. Access to video segments is provided by our new, multiscale segment. Given a set of training spatiotemporal graphs, W. Brendel et al learn their archetype graph associated with model nodes and edges. The model adaptively learns from data relevant video segments and their relations, addressing the "what" and "how." Inference and learning are formulated within the same framework – that of a robust, least-squares optimization – which is invariant to arbitrary permutations of nodes in spatiotemporal graphs. The model is used for parsing new videos in terms of detecting and localizing relevant activity parts. W. Brendel et al outperform the state of the art on benchmark Olympic and UT human-interaction datasets, under a favorable complexity. - Accuracy trade-off [7]. Graphical models have been used with great success to concisely capture the structure of an activity in terms of the hierarchy and spatiotemporal arrangement of its sub-activities. For example, activity structure has been modeled by Hidden Markov Model (HMMs), dynamic Bayesian nets [19], prototype trees, spatiotemporal graphs, context-free (AND-OR) grammars, CRFs, and compilations of first-order logic to graphical models. These approaches, however, typically define an activity in terms of pre-selected primitive actions, and manually specify their space-time relationships. A few methods learn relevant activity parts from data, but they fix their total number, and allow only the relation followed-by. More formally, they typically pre-specify the number of random variables (nodes) representing primitive actions, and their statistical dependences (edges), referred to as the model structure. Due to this heuristic model specification, in training, significant resources could be wasted on learning hand-picked parts and relations which may not be the most relevant for representing and recognizing the activity. These issues have recently been addressed by learning relevant contextual relations between individual actions of people in a group activity. However, their model encodes a fixed number of primitive actions Recognizing human activities in partially observed videos is a challenging problem and has many practical applications. When the unobserved subsequence is at the end of the video, the problem is reduced to activity prediction from unfinished activity streaming, which has been studied by many researchers. However, in the general case, an unobserved subsequence may occur at any time by yielding a temporal gap in the video. Y. Cao et al propose a new method that can recognize human activities from partially observed videos in the general case. Specifically, Y. Cao et al formulate the problem into a probabilistic framework: 1) dividing each activity into multiple ordered temporal segments, 2) using spatiotemporal features of the training video samples in each segment as bases and applying Sparse Coding (SC) to derive the activity likelihood of the test video sample at each segment, and 3) finally combining the likelihood at each segment to achieve a global posterior for the activities. Y. Cao et al further extend the proposed method to include more bases that correspond to a mixture of segments with different temporal lengths, which can better represent the activities with large intra-class variations. Y. Cao et al evaluate the proposed methods (SC and MSSC) on various real videos. Y. Cao et al also evaluate the proposed methods on two special cases: 1) activity prediction where the unobserved subsequence is at the end of the video, and 2) human activity recognition on fully observed videos. [9]. K. Shahid et al present a framework for the recognition of collective human activities. The framework provides a means to accurately classify human actions using the least amount of temporal information [12]. A collective activity is defined or reinforced by the existence of coherent behavior of individuals in time and space. K. Shahid et al call such coherent behavior 'Crowd Context'. Examples of collective activities are "queuing in a line" or "talking". Following, K. Shahid et al propose to recognize collective activities using the crowd context and introduce a new scheme for learning it automatically. The scheme is constructed upon a Random Forest structure which randomly samples variable volume spatio-temporal regions to pick the most discriminating attributes for classification. Unlike previous approaches, the algorithm automatically finds the optimal configuration of spatio-temporal bins, over which to sample the evidence, by randomization. This enables a methodology for modeling crowd context. K. Shahid et al employ a 3D Markov Random Field to regularize the classification and localize collective activities in the scene. K. Shahid et al demonstrate the flexibility and scalability of the proposed framework in a number of experiments and show that the method outperforms state-of-the art action classification techniques. [10]. A. Gupta et al also demonstrate the use of such constraints in recognition of actions from static images without using any motion information. [18]. An Activity Recognition Chain (ARC) is a sequence of signal processing, pattern recognition, and machine learning techniques that implements a specific activity recognition system behavior similarity to general-purpose pattern recognition systems but, also has a number of specific requirements and constraints.

III. PROPOSED SYSTEM

An Activity Recognition Chain is a sequence of signal processing, pattern recognition, and machine learning techniques that implement a specific activity recognition system behavior (see Figure.1). As can be seen from the figure, an ARC bears strong similarity to general-purpose pattern recognition systems but, as we will detail in the following sections, also has a number of specific requirements and constraints. The possible objectives of data mining, which are often called tasks of data mining [1] can be classified into some broad groups. Also, note that the chain can be executed in two different modes of operation if supervised classification algorithms are used, namely, training (modeling) and classification. Unsupervised classification doesn't require a dedicated training step but directly infers activities from the sensor data. Neural networks have good scope for nonlinear modeling of time series data [4]. A vast literature exists on prediction of time series, in a variety of domains [11].

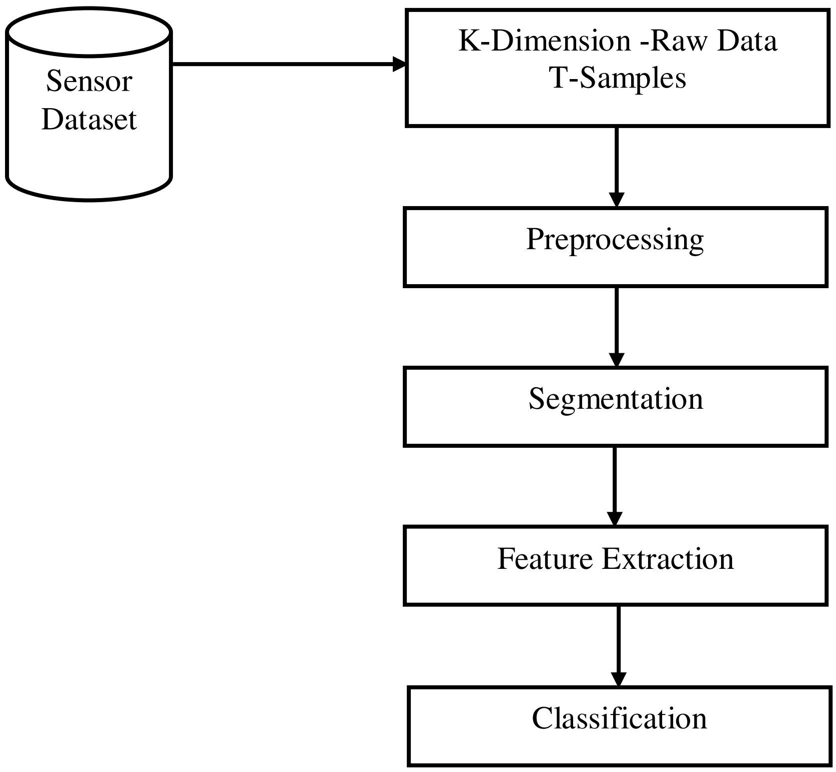

Fig. 1 Proposed System Architecture

• In the first stage of a typical ARC, raw data is acquired using several sensors attached to different locations on the body. In addition, advanced HAR systems may also include sensors placed in the environment.

• The pre-processing stage transforms the raw multivariate and non-synchronous time series data into a pre-processed time series.

• The data segmentation stage identifies those segments of the pre-processed data streams that are likely to contain information about activities (also often referred to as activity detection or "spotting").

• The feature extraction and selection stage reduces the signals into features that are discriminative for the activities at hand. Features may be calculated automatically and/or derived based on expert knowledge.

• Software Project Management (SPM) algorithm mines the sequence database looking for repeating patterns (known as frequent sequences) that can be used later by the end-users to find associations between different items or events in their data for purposes such as marketing campaigns, web usage mining [15].

IV. Results And Discussion

Activity recognition has adopted several performance metrics that have proven to be beneficial in other fields, such as confusion matrices; related measures such as accuracy, precision, recall, and F-scores; or decision-independent Precision-Recall (PR) or Receiver

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Operating Characteristic (ROC) curves. For further details on metrics specifically geared toward activity recognition. This summarize some common metrics that are frequently used in activity recognition research.

A. *Confusion Matrix*

A confusion matrix summarizes how many instances of the different activity classes got confused (i.e., misclassified) by the system. Typically, the rows of a confusion matrix show the number of instances in each actual activity class (defined by the ground truth), while the columns show the number of instances for each predicted activity class (given by the classifier's output). Each row of the matrix is filled by comparing all ground truth instances of the corresponding actual class with the class labels predicted by the system. From the matrix, precision (TPTP+FP) and recall (TPTP+FN) values as well as the overall accuracy (TP+TNall) and the harmonic mean of precision and recall, the F1 score (2∗precision∗recall/ precision + recall), can be calculated for each activity class. If a dataset is unbalanced (i.e., the number of ground truth instances of the activity classes vary significantly), the overall accuracy is not representative of the true performance of a classifier. The number can be strongly biased by dominant classes, usually the less relevant background class. To address this "class skew" problem, normalized confusion matrices should be used to allow for objective comparison between the different activity classes. Instead of absolute counts of instances, a normalized confusion matrix shows the confusion as a percentage of the total number of ground truth activity instances.

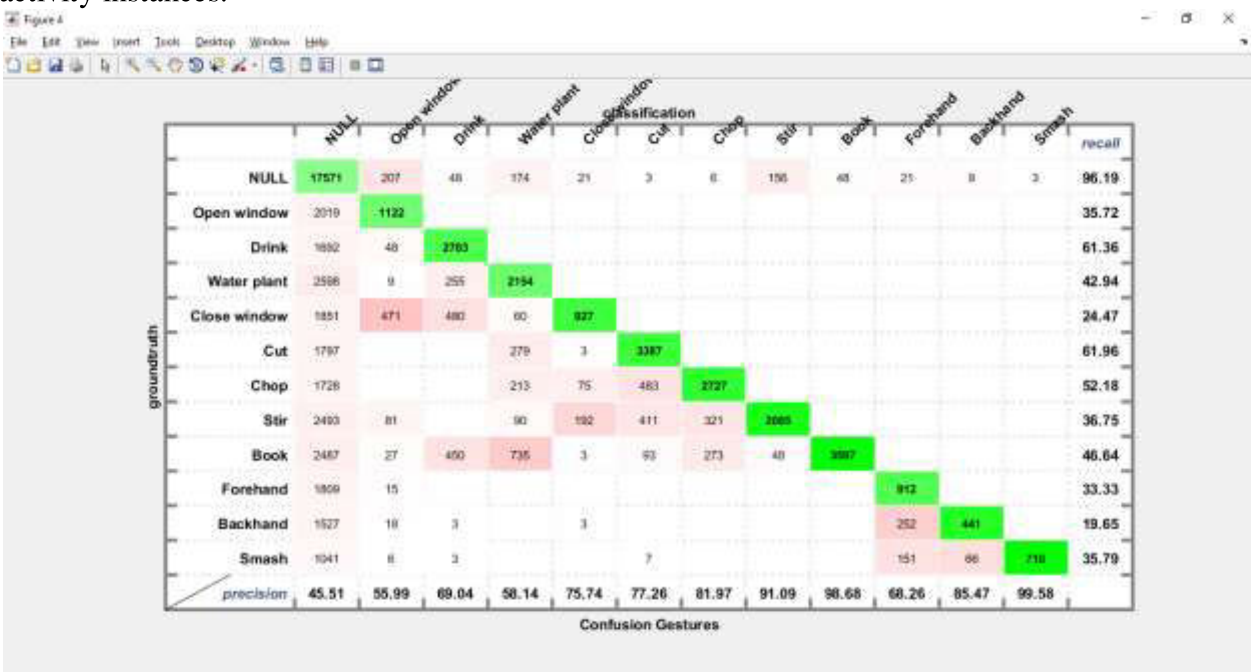

Fig. 2 Confusion Matrix of Arm Movement

B. *ROC and PR Curves*

It is often difficult to set the optimal decision threshold on the classifier's score beforehand. Therefore, a common strategy is to sweep the threshold on the score for each individual class (one vs. all) and analyze the behavior in so-called Receiver Operating Characteristic (ROC) or Precision-Recall (PR) curves. ROC curves plot the true positive rate (recall) against False-Positive Rate (FPR) (FP/FP+TN). Typically, lowering the decision threshold increases the recall and respectively the FPR. Best-case results approach the top left corner, while worst case (i.e., random) results follow the diagonal if class distributions are balanced. AsROC curves depend on TN counts, imbalanced class distributions (i.e., percentage of relevant activity vs. percentage of all other activities including NULL) may lead to "overoptimistic" ROC curves. PR curves do not depend on the true negative count. Therefore, they are suited to detection tasks, where activities of interest are "buried" in a large corpus of irrelevant data (NULL class). Similarly, to ROC curves, lowering the decision threshold results in an increased recall and typically decreases the precision by increasing false positives.

Several metrics can be extracted from ROC and PR curves to summarize them into a single and thus more easily comparable number. Equal Error Rate (EER) represents the point in the PR curve where precision equals recall. The higher this value, the better. Another measure is average precision. Precision is measured at uniform steps (e.g., 10% steps) of the recall and subsequently averaged. Finally, the Area under Curve (AUC) can be calculated from ROC curves as a measure to describe the overall performance of a classifier. The AUC is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

TABLE I: COMPARISON OF ROC PERFORMANCE WITH TRUE POSITIVE RATE

Algorithm	**TPR**							
	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6
Sequential Pattern Mining	0.24	0.37	0.46	0.57	0.67	0.71	0.78	0.84
Proposed	0.34	0.56	0.68	0.74	0.79	0.86	0.93	0.95

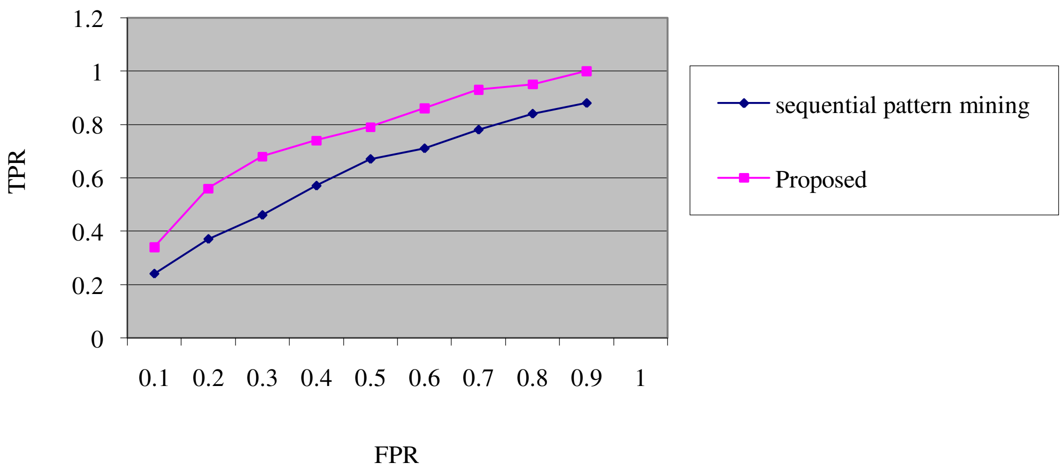

Fig.3. Comparison of different frame sequences with true positive rates

V. CONCLUSION

The proposed research challenges that human activity recognition shares with general pattern recognition and identify those challenges that are specific to human activity recognition. It then describes the concept of an Activity Recognition Chain as a general-purpose framework for designing and evaluating activity recognition systems. The framework comprises components for data acquisition and preprocessing, data segmentation, feature extraction and selection, training and classification, decision fusion, and performance evaluation. The proposed system concludes with the example problem of recognizing different hand gestures from inertial sensors attached to the upper and lower arm. It illustrates how each component of this framework can be implemented for this specific activity recognition problem and demonstrate how different implementations compare and how they impact overall recognition performance. The future work focus low complexity of the example allowed us to compare different algorithms with respect to overall recognition performance, which hope will prove helpful to newcomers also for designing more complex activity recognition systems.

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