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ABSTRACT

In this paper, we present an approach for detection of spam calls over IP telephony called SPIT in Voice-over-IP (VoIP) systems. SPIT detection is different from spam detection in email in that the process has to be soft real-time, fewer features are available for examination due to the difficulty of mining voice traffic at runtime, and similarity in signaling traffic between legitimate and malicious callers. Our approach differs from existing work in its adaptability to new environments without the need for laborious and error-prone manual parameter configuration. We use clustering based on the call parameters leveraging optional user feedback for some calls, which they mark as SPIT or non-SPIT. We improve on a popular algorithm for semi-supervised learning, called MPCK-Means, to make it scalable to a large number of calls. Our evaluation on captured call traces shows a fifteen fold reduction in computation time, with improvement in detection accuracy.

Keywords

Voice-over-IP systems, spam detection, spit detection, semi-supervised learning, clustering

1. INTRODUCTION

As the popularity of VoIP systems increases, they are being subjected to different kinds of security threats [1]. A large class of the threats such as call rerouting, toll fraud, and conversation hijacking incur deviations in the protocol state machines and can be detected through monitoring the protocol state transitions [2],[3]. Additionally, cryptographically secure versions of the common VoIP protocols, such as Secure SIP and Secure RTP, address many of the attacks presented in the literature. However, spam calls in VoIP [4], commonly called SPIT, are becoming an increasing nuisance. The ease with which automated SPIT calls can be launched can derail the adoption of VoIP as a critical infrastructure element. Existing monitoring and cryptographic solutions are not immediately applicable to SPIT detection. In this paper, we address the problem of detection of SPIT calls.

Detection of spam emails is a mature field and there are some similarities to our problem. In both domains, users can provide feedback about individual email or call, often through a built-in button in commercially available VoIP phones. However, there exist significant differences – VoIP traffic is real-time and the detection should ideally be real-time as well, some features are expensive to extract in real-time, specifically those in the voice media traffic, the signaling patterns are likely similar in legitimate and malicious calls rendering content-based filtering on signaling traffic ineffective, and features from multiple protocols used in VoIP may be relevant.

In this paper, we present the design of a system that uses semi-supervised machine learning for detection of SPIT calls. It builds on the notion of clustering whereby calls with similar features are placed in a cluster for SPIT or legitimate calls. Call features include those extracted directly from signaling traffic such as the source and destination addresses, extracted from media traffic, such as proportion of silence, and derived from calls, such as duration and frequency of calls. Approaches that use thresholds [5] on the call features are difficult to use in practice since the nature of SPIT calls varies widely.

The popular semi-supervised clustering algorithm called MPCK-Means [6] scales as $O(N^3)$ where N is the number of calls. This would generally be too expensive for real-time operation. We modify this to create our algorithm called eMPCK-Means, using VoIP specific features to reduce it to $O(N)$. Such specialization includes the early use of user feedback and prior knowledge of the number of clusters. Additionally, we create an incremental protocol called pMPCK-Means, that can perform the detection as soon as the call is established providing the option of automatically hanging up a suspect call.

We evaluate the protocols using four call traces with different characteristics of SPIT and non-SPIT calls, over different proportions of user feedback and accuracy of the user feedback. With a batch of 400 calls, eMPCK-Means is 15 times faster than MPCK-Means, while achieving better detection coverage in terms of true and false positives. Since pMPCK-Means can examine a limited set of call features, it works well only with a large fraction of calls with accurate user feedback.

2. RELATED WORK

Rosenberg [4] details the problem of VoIP SPIT and gives various high-level conceptual solutions. The solutions can be placed in three categories [7]: (1) Non-intrusive methods based on the exchange and analysis of signaling messages; (2) Interaction methods that create inconveniences for the caller by requesting her to pass a checking procedure before the call is established; (3) Callee interaction methods that exchange information with the callee on each call. An example work in category 1 is [8] where the authors look at the SIP signaling traffic pattern to detect SPIT. However, they do not provide quantitative data on the detection accuracy. Our experimental results indicate solely relying on SIP message patterns will give low detection coverage. The work by Quittek [7] generates a greeting sound or faked ring tone to the caller right after the call is established and monitors the response voice patterns from the caller to differentiate between human

caller and a SPIT generator. This falls in category 2. In comparison, our work encompasses categories 1 and 3.

Kolan [9] presents an approach based on trust, reputation, and social networking. They maintain the trust information for each caller, which can be automatically built up through user feedback, or through a propagation of reputation via social networks. Their approach can be used with our work in which we can embed the caller's trust as one of the dimensions in our call data points. A distinction between their work and ours is that their approach is tied with each caller, while our approach looks at each phone call directly. The size of the reputation database may grow large and a reputation system can be gamed by false praise or false negative ratings.

For spam detection in email, the family of Naive Bayes (NB) classifiers [10],[11] is probably one of the most commonly implemented. They extract keywords and other indicators from email messages and determine whether the messages are spam using some statistical or heuristic scheme. However, spammers nowadays are using increasingly sophisticated techniques to trick content-based filters by clever manipulation of the spam content, leading to a virtual arms race. Recent work [12],[13] has used features for the senders extracted from social networks in supervised learning or in creating white/blacklists. Supervised learning relies on a training phase with accurate training data, while our approach does not.

Clustering is a way to learn a classification from the data [14], especially with unlabelled data. Clustering techniques have been used on detecting e-mail spam by [15] and [16]. On the other hand, classification techniques such as SVM[17] is a popular approach for doing data classification. However, they typically require labeled data and doesn't take unlabelled data into consideration. Recent development on semi-supervised classification techniques [18] such as semi-supervised SVM[19] addresses this.

3. DESIGN

3.1 Structure of VoIP calls

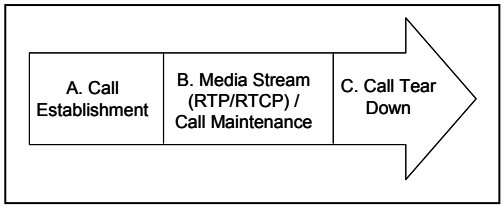


Figure 1. Three phases in a VoIP call

Figure 1 shows the typical three phases involved in a VoIP phone call [20]. The first phase is call establishment through a three-way handshake, which involves the caller sending SIP INVITE messages to the proxy server, the server forwarding the INVITE message to the callee, the callee replying with SIP OK message, and eventually SIP ACK message to complete the call establishment phase. The second phase is the conversation, which contains the media stream (voice) transmitted between the caller and the callee typically using RTP/RTCP [21]. The last phase is the call tear down phase, which can be initiated by either the caller or the callee sending SIP BYE messages followed by SIP OK and SIP ACK messages.

3.2 Characteristics of VoIP SPIT calls

In this section, we elaborate on the different patterns one can perceive between SPIT and non-SPIT calls.

3.2.1 Look at each individual call

When looking at each individual call, both SPIT and non-SPIT calls follow the same three phases described in Sec. 3.1. From the call establishment phase, the only possible differences one can really tell is the source IP and the From URI in the SIP INVITE (the phone number of the caller/spitter). There may be differences in the User-Agent field and the SDP part in the SIP INVITE if the phones used by the spitter are of a different model than the ones used by legitimate users. However, this is a dubious characteristic to base the determination on. In general, one can only resort to a blacklist-based approach to distinguish between SPIT calls and non-SPIT calls when looking at the call establishment phase.

In the media stream phase, a typical pattern one can imagine for SPIT calls is that the caller tends to speak more than the callee. Another pattern is that the length of the media stream phase, i.e., the call duration, could be shorter in the case of calls answered by a live person since SPIT calls are generally undesirable.

The call tear down phase involves the same SIP BYE/OK/ACK messages for SPIT and non-SPIT calls. A possible difference though is which of the two parties hangs up the call first, which translates to which side sends the SIP BYE message. Assuming SPIT calls are undesirable, one can assume that it's more likely that a call will be hung up by the callee.

This mode of looking at individual calls would be useful to an individual consumer who would be helped by a SPIT call being dropped without her having to pick up the call. The challenge here is what would be the appropriate threshold values on the different call features to determine if a call is SPIT or not. We believe that due to the diversity of SPIT calls, it is dangerous to use static thresholds for any of the call features. This prompted us to explore more dynamic schemes that automatically adapt to changing call patterns.

3.2.2 Look at the whole batch

Since SPIT calls are usually large volume calls made by some spitter within a period of time, we found that it is also useful to look for the corresponding pattern in a batch of calls. Certain features are available when looking at the collective set of calls. These include the inter-arrival time between calls, the density of calls, etc. This mode would be useful say to a service provider that is interested in identifying and blacklisting sources of SPIT calls in its networks.

3.3 The detection scheme

A VoIP environment typically consists of multiple domains with each domain composed of a few proxy servers and phones belonging to end users. The phones can be soft phones (a general purpose computer with appropriate software) or hard phones (hardware for making and receiving VoIP calls). The two dominant signaling protocols used in VoIP are H.323 and SIP, with the latter becoming increasingly dominant. Figure 2 shows an example VoIP environment consisting of two domains. In a VoIP environment, a proxy server's main function is to route the signaling messages. For the specific example we show, here Proxy #1 is used to route the signaling messages among phones {A,B,C}. And similarly, Proxy #2 is used to route the signaling messages among phones {E,F}. Cross domain phone calls

{A,B,C} ⇄ {E,F} are collaboratively handled by Proxy #1 and Proxy #2. Once a phone call is established, subsequent signaling messages can possibly travel directly between phones not via the proxies. However, an ISP can mandate all signaling traffic through the proxies, which is usually the case for billing/security purposes.

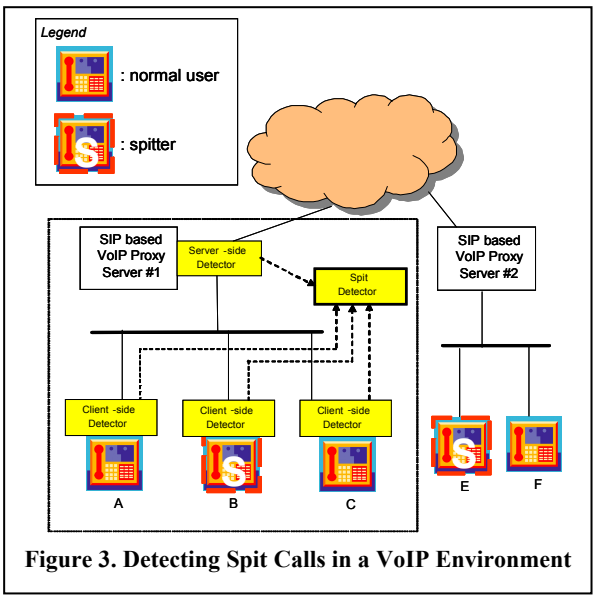


Figure 3. Detecting Spit Calls in a VoIP Environment

The media streams following call establishment are usually transmitted directly between the phones such that the workload on the server can be reduced. However, it is also possible to let the servers proxy the media streams as well. This is used when transcoding of the media stream is required (e.g. the two phones do not use the same codec.) and for security and accounting purposes.

Our approach in detecting SPIT calls involves placing local detectors at the SIP Proxy and the phones in the managed domain. Essentially, the detectors observe the signaling and media streams within the domain no matter they are proxied or sent directly from end to end. The domains that have our detection mechanism are called managed domains and others are called unmanaged domains. We assume a spitter can exist as any phone in a VoIP environment, whether within a managed (phone B) or an unmanaged domain (phone E).

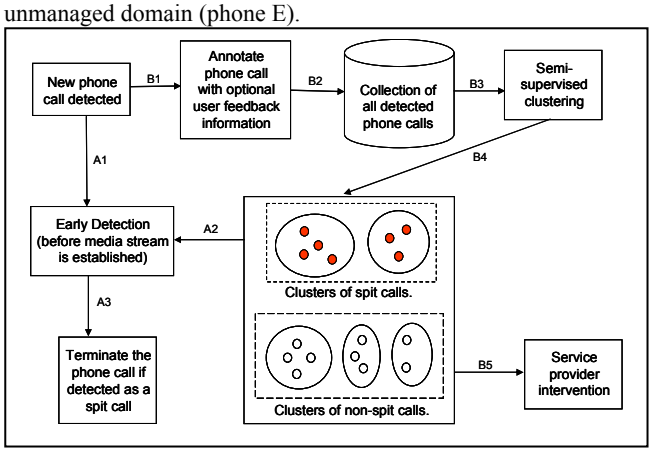


Figure 2. Process flow in SPITDetector

The detectors embedded at the server and the phones collect the information of the phone calls and send them to the SPITDetector, which is the place where the logic on differentiating SPIT calls from non-SPIT calls executes. The information about a phone call may include From URI (caller identity), To URI (callee identity), silence duration in the RTP media streams, etc. Since the decoding of these information are handled by the respective server-side/client-side detectors and only a digest of the necessary information is forwarded up to the SPITDetector, network traffic is minimized. If scalability becomes an issue, we can divide a domain into sub-domains and have separate SPITDetectors perform detection for phone calls within each sub-domain concurrently. User feedback about calls can be shared between the sub-domains within one domain. Our approach accommodates incremental deployment in that clients in managed domains will have detection of SPIT calls, whether they originate from managed or unmanaged domains.

Essentially, our problem is a data classification problem, where we want to classify phone calls into SPIT calls and non-SPIT calls. In the SPITDetector, we employ a semi-supervised clustering technique, which is one of the recent data classification approaches [22]. Figure 2 shows the process flow involved in the SPITDetector, which supports two modes of detection:

Mode A: Look at each phone call with early detection

In this mode, the SPITDetector has to determine whether a call is a SPIT or not before the media stream of the call is established. This means that the detection has to be completed before the callee picks up the phone. This mode is useful from an end-user's point of view since SPIT calls can be potentially blocked without further annoyance.

In Figure 2, path A1 represents the extraction of features (call characteristics) of a call during the call establishment phase (Sec. 3.1). The features are therefore limited to source IP, From URI, To URI, and start time of the call (Sec. 3.2.1). The detection is carried out through calculating the distance of the call in question with the current SPIT/non-SPIT clusters (Sec. 3.5). If the call is closer to the SPIT cluster in terms of the distance metric, it will be regarded as a SPIT call via path A3, which leads to the termination of the phone call.

Mode B: Look at the whole batch of phone calls

With Mode B, we assume received calls are kept in a collection through Path B1 and B2. The calls in the collection are then presented in a batch to the semi-supervised clustering algorithm. This detection mode provides higher detection accuracy than Mode A due to the availability of complete call feature information. Due to the interactive nature of VoIP calls, Mode B is probably not as attractive to an end-user as the detection is carried out after a phone call is completed. However, we see possible application from a service provider's perspective, who can resort to actions against those accounts that have been involved in placing SPIT calls. This can be used together with legislative measures in place for punitive actions against those who violate the do-not-call list or target SPIT calls to cell phones. Also, an accurate identification of SPIT activities can be an integral part of system performance monitoring.

3.4 SPIT Detection using Semi-Supervised Clustering

3.4.1 Clustering & Semi-Supervised Clustering: Background

Clustering is a popular approach for data classification which groups data points into clusters such that points in the same cluster are more similar to each other than to points in the other clusters according to some defined criteria [23]. For example, the classical K-Means algorithm [14] clusters N data points $\{x_1,x_2,\ldots,x_N\}$ into K clusters $\{X_1, X_2,.., X_K\}$ with centroids $\{\mu_1, \mu_2, \ldots, \mu_K\}$. The corresponding objective function is that:

$$\sum_{j=1}^{K}\sum_{x_i \in X_j} \left\| x_i - \mu_i \right\|^2 \quad \text{is minimized} \tag{1}$$

In our problem context, each VoIP call is regarded as one data point. We are interested in clustering call data points into two clusters, one containing the SPIT call data points, and the other containing the non-SPIT call data points. In general, there may be multiple sub-clusters within each cluster corresponding to radically different kinds of SPIT or non-SPIT calls. We explore this approach of multiple sub-clusters further in Sec. 3.7.

There is abundant existing work, such as [15] and [16], on applying clustering techniques to identify e-mail spam, which further motivates our attempt on applying clustering technique for solving the VoIP SPIT detection problem. Classically clustering is regarded as an unsupervised data classification technique. This means that except for the criteria (like Eq. (1) for K-Means), there is no need to provide some labeled data in advance as the training set. In classical K-Means, each dimension of the data point vector x_i is regarded as equally important in the Euclidean distance calculation. This implies that only the most relevant features should be converted to a dimension in a data point vector since the other less-relevant features will act as noise in the clustering process and will result in poorer clustering quality.

Semi-supervised clustering [22], [24], [6] is a recent development in the data clustering research community that aims to address the aforementioned issue on selecting the proper criteria for clustering. Semi-supervised clustering allows the use of optional labeled data for a subset of the observations seen at runtime to progressively modify the clustering criteria. This means that one does not need to worry about which features should go into the data point and which should not. The clustering criteria will be trained into generating clusters that obey the user-labeled data as faithfully as possible [6]. The implicit assumption is that user feedback is perfectly accurate. In our work here, we evaluate the impact of noise in the user feedback.

3.4.2 Features of a VoIP call for identifying patterns of SPIT calls

We construct a data point for each VoIP call based on 17 features : 1.From URI, 2.To URI, 3.Start time, 4. Duration, 5.# of SIP INVITE messages, 6.# of ACK messages, 7.# of BYE messages from caller, 8.# of BYE messages from callee, 9. Time since the last call from the originator of the current call, 10-15.# of 1xx, 2xx, 3xx, 4xx, 5xx, and 6xx SIP Response messages, 16.Call frequency of the originator of the current call, 17.Ratio of the non-silence duration of the callee media stream over the caller media stream.

For Mode A early detection (Sec. 3.3), only features 1, 2, 3, and 9 are available. Feature 17 is derived from the RTP media stream by client-side detectors if the media streams are configured to flow directly between clients [25] or it can be provided by the server-side detector if the media streams are configured to flow through the SIP Proxy.

In our design, expert knowledge on the representativeness of each feature for identifying a SPIT call is not a known priori. The design relies on semi-supervised clustering to automatically reweighting the importance of each feature in the runtime. We select features which roughly cover different facets of a VoIP call and attempt to keep a small number of features to limit the involved time/space complexities in the clustering process.

3.4.3 User feedback as labeled data for semi-supervised clustering

As mentioned earlier, semi-supervised clustering allows user labeled data to be supplied to train the clustering criteria. Here, we assume phone calls received in the managed domain (A and C in our example Figure 2) can have optional user feedback information indicating whether a call is a SPIT call or a non-SPIT call. The corresponding data point will be labeled with a SPIT or a non-SPIT tag and fed into the semi-supervised clustering process. In the ideal case, the effect is that the clustering process will intelligently group all SPIT calls into one cluster and group non-SPIT calls into the other cluster and also identify which call features are useful in making this distinction.

The use of user feedback and semi-supervised clustering enables our detection scheme to adapt to different environments. For example, in a corporate internal VoIP system, high frequency calls could be a common case for non-SPIT calls, while in a household community VoIP system, high frequency calls could be an indicator for SPIT calls. The user feedback can be implemented as a Yes/No button on the phone for the user to press to indicate a received phone call as SPIT/non-SPIT [26]. In general, we argue against the use threshold-based or static rule-based schemes for detection of SPIT calls in VoIP environments.

3.4.4 Extended K-Means for semi-supervised clustering: MPCK-Means

For this work, we select the semi-supervised clustering algorithm called MPCK-Means [6].

$$\begin{aligned}\tau_{\text{mpckm}} = &\sum_{\mathrm{x}_i \in \chi}\left(\left\|\mathrm{x}_i - \mu_{l_i}\right\|^2_{\mathrm{A}_{l_i}} - \log\left(\det\left(\mathrm{A}_{l_i}\right)\right)\right) \\ &+ \sum_{(\mathrm{x}_i,\mathrm{x}_j)\mathrm{x}_i \in M} w_{ij} f_M\left(\mathrm{x}_i,\mathrm{x}_j\right) 1\left[l_i \neq l_j\right] \\ &+ \sum_{(\mathrm{x}_i,\mathrm{x}_j)\mathrm{x}_i \in C} \overline{w_{ij}} f_C\left(\mathrm{x}_i,\mathrm{x}_j\right) 1\left[l_i = l_j\right]\end{aligned} \tag{2}$$

$$\left\|\mathrm{x}_i - \mu_i\right\|^2_{\mathrm{A}_{l_i}} = \left(\mathrm{x}_i - \mu_i\right)^{\mathrm{T}} \mathrm{A}_{l_i}\left(\mathrm{x}_i - \mu_i\right) \tag{3}$$

$$f_M\left(\mathrm{x}_i,\mathrm{x}_j\right) = \frac{1}{2}\left\|\mathrm{x}_i - \mathrm{x}_j\right\|^2_{\mathrm{A}_{l_i}} + \frac{1}{2}\left\|\mathrm{x}_i - \mathrm{x}_j\right\|^2_{\mathrm{A}_{l_j}} \tag{4}$$

$$f_C\left(\mathrm{x}_i,\mathrm{x}_j\right) = \left\|\mathrm{x}'_{l_i} - \mathrm{x}''_{l_i}\right\|^2_{\mathrm{A}_{l_i}} - \left\|\mathrm{x}_i - \mathrm{x}_j\right\|^2_{\mathrm{A}_{l_j}} \tag{5}$$

$$
\begin{aligned}
\mathrm{A}_h = |X_h| \Bigg(& \sum_{x_i \in X_h} (x_i - \mu_h)(x_i - \mu_h)^T \\
& + \sum_{(x_i, x_j) \in M_h} \frac{1}{2} w_{ij} (x_i - x_j)(x_i - x_j)^T \, 1[l_i \neq l_j] \\
& + \sum_{(x_i, x_j) \in C_h} \Big(\overline{w_{ij}} (x_h^{'} - x_h^{''})(x_h^{'} - x_h^{''})^T \\
& - (x_i - x_j)(x_i - x_j)^T \, 1[l_i = l_j] \Big) \Bigg)^{-1}
\end{aligned} \tag{6}
$$

Eq. (2) is the objective function in MPCK-Means. l_i is the cluster that point x_i is associated with. The main idea is the same as classic K-Means where intra-cluster distance is being minimized. However the Euclidean distance metric in MPCK-Means is weighted by a cluster-specific matrix A_{li} (one can also use the same A matrix across all clusters. [6]). A_{li} is modified based on user feedback and points in cluster l_i following Eq. (6).

The user labeled data in MPCK-Means is supplied in the form of clustering constraints M (must link sets) and C (cannot link set). Here M set specifies pairs of data points that should be put in the same cluster while the C set specifies those pairs of data points that should not be put in the same cluster. In (2), the last two terms are used to add penalty to the objective function from the violation of the constraints. The function f_M returns a value proportional to the distance between the two points that are in different clusters. The function f_C returns a value that is inversely proportional to the distance between two points that are in the same cluster. The points x_{li}' and x_{li}'' represent the two farthest data points in X_{li} with respect to their distance computed using A_{li}. The pseudo code for MPCK-Means is listed as Algorithm 1.

Algorithm: MPCK-Means

Input: Set of data points $X = \{x_i\}_{i=1}^{N}$, Set of must-link constraints $M = \{(x_i, x_j)\}$, Set of cannot-link constraints $C = \{(x_i, x_j)\}$, Number of clusters K, sets of constraints costs W and $\overline{W}$, $t \leftarrow 0$.

Output: Disjoint K-partitioning $\{X_h\}_{h=1}^{K}$ of X such that objective function τ_{mpckm} is locally minimized.

Method:

1. Initialize clusters:

1.1. Create the λ neighborhoods $\{N_P\}_{P=1}^{\lambda}$ from M and C.

if $\lambda \geq K$

Initialize $\{\mu_h^{(0)}\}_{h=1}^{K}$ using weightiest farthest-first traversal starting from the largest N_P.

Else

initialize $\{\mu_h^{(0)}\}_{h=1}^{\lambda}$ with centroids of $\{N_P\}_{P=1}^{\lambda}$

initialize remaining clusters at random

2. Repeat until convergence

2.1. For each data point $x_i \in X$

$$
h^* = \arg\min_h \Big(\|x_i - \mu_h^{(t)}\|_{\mathrm{A}_h}^2 - \log(\det(\mathrm{A}_h)) + \sum_{(x_i, x_j) \in M} w_{ij} f_M(x_i, x_j) 1[h \neq l_j] + \sum_{(x_i, x_j) \in C} \overline{w_{ij}} f_C(x_i, x_j) 1[h = l_j] \Big)
$$

Assign x_i to $X_{h^*}^{t+1}$

2.2. For each cluster X_h, $\{ \mu_h^{(t+1)} \leftarrow \frac{1}{|X_h^{t+1}|} \sum_{x \in X_h^{t+1}} x \}$

2.3. Update_metrics A_h for all clusters $\{X_h\}_{h=1}^{K}$ (Eq. (6))

2.4. $t \leftarrow t + 1$

Algorithm 1. MPCK-Means (Adapted from [6])

3.4.5 Mapping user feedback to pair-wise constraints in MPCK-Means

The user feedback model is that a user (the callee) in the managed domain can optionally indicate whether a received phone call is a SPIT or not. For the corresponding data point x_i, the user indicates $x_i \in F_S$ for a SPIT call and indicates $x_i \in F_N$ for a non-SPIT call. The system keeps two sets: F_S (data points of SPIT calls from feedback) and F_N (data points of non-SPIT calls from feedback). With respect to the MPCK-Means algorithm, must-link constraints M are derived online from pairs of points $(x_i, x_j) \in F_S$ or $(x_i, x_j) \in F_N$. Similarly, cannot-link constraints C are created online from (x_i, x_j), where $x_i \in F_S$ and $x_j \in F_N$.

For ease of exposition, we initially discuss the case with 2 clusters—one for SPIT and the other for non-SPIT calls. We discuss the extension to consider multiple clusters for SPIT / non-SPIT calls in Sec. 3.7.

3.4.6 Building detection predicate based on cluster associations

Given a cluster X_h from the clustering algorithm, we use the majority of the data points with user feedback in the cluster to determine the association of the cluster. If $|X_h \cap F_S| > |X_h \cap F_N|$, the calls in X_h will be considered SPIT calls; otherwise, they will be considered non-SPIT calls.

3.5 eMPCK-Means (Efficient batch-mode MPCK-Means)

In the cluster assignment step of MPCK-Means (Step 2.1) the time complexity on iterating through the must-link/cannot-link peers of point x_i is a O(N) operation. X is the whole set of data points supplied to the clustering algorithm. N=|X| is the number of data points. The determination of the maximally separated points $x_h^{'}$ and $x_h^{''}$ used in $f_c(.)$ (Step 2.1 of Algorithm 1) and update_metrics (Step 2.3) has time complexity O(N^2). This implies MPCK-Means is O(N^3) since the operation has to be done for each data point. Thus, MPCK-Means does not scale well with large data sets. For our application, where N can be hundreds for a small-sized domain or thousands for a mid-sized domain, it turns out to be prohibitive time-wise to apply the original MPCK-Means directly.

Therefore, we adapt MPCK-Means into the eMPCK-Means (efficient MPCK-Means) algorithm, with the maximally separated points estimated through an O(1) approximation algorithm. We use an O(N) implementation for the neighborhood creation process in the cluster initialization step of MPCK-Means. Additionally, the general practical experience with a K-Means based algorithm is that it converges within a small number of iterations for the main loop Step 2 in MPCK-Means. Combined these make eMPCK-Means linear time complexity with respect to

the number of data points N and the constant is small for a range of VoIP call traces.

3.5.1 eMPCK-Means : Initialize clusters

The eMPCK-Means algorithm creates the initial neighborhoods directly from the user feedback F_S and F_N sets. Specifically, it creates w neighborhoods $\{F_S, F_N, x_{n3}, x_{n4}, \ldots, x_{nw}\}$, where $\{x_{n3}, x_{n4}, \ldots, x_{nw}\} = X\text{-}F_S\text{-}F_N$ is the set of data points not covered by the user feedback. The complexity of this step is O(N). We use the same weighted-farthest-first traversal as in MPCK-Means, which is O(N) when the number of clusters is a constant [27]. Overall, the initialize clusters in eMPCK-Means has O(N) complexity.

3.5.2 eMPCK-Means : efficient estimation of maximally separated points $\left(x_h^{'}, x_h^{''}\right)$

In MPCK-Means, to find the exact maximally separated points $\left(x_h^{'}, x_h^{''}\right)$ used in Eq. (5) and Eq. (6), it requires evaluating the distance $\left\|x_i - x_j\right\|_{\mathrm{A}_h}^2$ for every pair of points $(x_i, x_j) \in X$, which is an O(N^2) operation. Since the matrix $\mathrm{A_h}$ is updated in each iteration of the loop of step 2 in Algorithm 1, this evaluation has to be repeated as well.

In eMPCK-Means, we estimate the maximally separated points by first putting data points from X into an array R[1..N] in a random ordering. We then iterate through consecutive elements R[i] and R[i+1] in the array. We set $\left(x_h^{'}, x_h^{''}\right)$ to (R[i'], R[i'+1]) that gives the maximal value of $\left\|\mathrm{R}[i'] - \mathrm{R}[i'+1]\right\|_{\mathrm{A}_h}^2$. This operation (Step 2, Algorithm 2) is performed once right after the cluster initialization step. The time complexity of this step is O(N).

However, since the A_h matrix is updated in each iteration of MPCK-Means (Step 2.3, Algorithm 1), the estimate $\left(x_h^{'}, x_h^{''}\right)$ has to be updated accordingly as well. We embed the updating process into the calculation of the parameterized Euclidean distance $\left\|x_i - x_j\right\|_{\mathrm{A}_h}^2$ (Eq. (3)). The parameterized Euclidean distance is calculated in Eq. (4) and Eq. (5) as well. The idea here is that when a pair of points (x_i, x_j) is found to have a greater distance than the current estimate $\left(x_h^{'}, x_h^{''}\right)$ at the time of evaluating the parameterized Euclidean distance, we will set the maximally separately points estimate to (x_i, x_j). The advantage of this approach is that it is an O(*1*) operation and does not increase the order of complexity of the eMPCK-Means algorithm. However, this is an approximation because suppose, in the loop to iterate through all the points, we are at point x_A and are calculating $\|x_A\text{-}x_B\|^2$. The point x_C is to be considered in a later iteration and (x_A, x_C) happens to be the farthest pair of points. Then, the computation for point x_A will not have the accurate distance for the farthest pair of points. Hereafter, when we refer to Euclidean distance computation, we mean that it has maximally separated point estimation embedded within it.

To insure that $f_C(.)$ function (Eq. (5)) does not evaluate to negative values with our approximated estimation of $\left(x_h^{'}, x_h^{''}\right)$, we enforce that the second term is always evaluated before the first term so that there is an opportunity to update $\left(x_h^{'}, x_h^{''}\right)$.

3.5.3 Use only a fixed number of constraints in cluster assignment step

In the cluster assignment step of MPCK-Means (Step 2.1, Algorithm 1), rather than iterating through the complete must-link/cannot-link peers of x_i, which makes Step 2.1 O(N^2), we choose a fixed sized subset of them. This corresponds to Step 3.1 in eMPCK-Means (Algorithm 2). This optimization is hinted at by the fact that the must-link/cannot-link information in our domain has significant redundancy. A set of k_1 and k_2 calls placed, through user feedback, in the SPIT and non-SPIT categories generates $k_1^2+k_2^2$ must-link and k_1k_2 cannot-link constraints. On the other hand, we see from experiment results by [6] that MPCK-Means can work reasonably well even with limited numbers of constraints. Together with the O(1) complexity maximally separated points estimation, the overall time complexity on the cluster assignment step is brought down to O(N). In general, this can negatively affect the clustering quality. However, we believe it is a trade-off that is necessary in an effort to make the detection scheme scalable. In the following, we will discuss about a domain specific optimization which can *improve* the detection quality over MPCK-Means for the cases with limited numbers of constraints.

3.5.4 Pre metrics update on the starting cluster(s)

In MPCK-Means, the first update metrics step (Step 2.3) occurs only after the first iteration of the cluster assignment step (Step 2.1). In the first iteration of the cluster assignment, a default identity matrix is assigned to A_h, which directly affects the quality of the generated clusters from the first iteration and has a long-term effect on the quality of the eventual clusters as we see empirically. Therefore, in eMPCK-Means we conduct a metrics update (Step 1.2, eMPCK-Means, Algorithm 2) early on, right after the initial clusters are generated from the cluster initialization step (Step 1.1, Algorithm 2). Intuitively, the user feedback is available at the outset and this optimization allows the A_h matrix to immediately adapt to the user feedback at the beginning, which results in more precise clustering. Based on our experiments, this improves the clustering quality and the detection accuracy of eMPCK-Means over the original MPCK-Means. Additionally, it improves the convergence speed of the algorithm as we see later (Table 1).

Algorithm: eMPCK-Means

Input: Set of data points $X = \{x_i\}_{i=1}^{N}$, Set of must-link constraints $M = \{(x_i, x_j)\}$, Set of cannot-link constraints $C = \{(x_i, x_j)\}$, Number of clusters K, sets of constraints costs W and $\overline{W}$, Optional initial cluster centroids $\{\mu_h^{(0)}\}_{h=1}^{K}$, $t \leftarrow 0$

Output: Disjoint K-partitioning $\{X_h\}_{h=1}^{K}$ of X such that objective function τ_{mpckm} is locally minimized.

Method:

1. If initial cluster centroids $\{\mu_h^{(0)}\}_{h=1}^{K}$ is not given in the input

1.1. Create the λ neighborhoods $\{N_P\}_{P=1}^{\lambda}$ with steps from Sec. 3.5.1.

if $\lambda \geq K$

Use weightiest farthest-first traversal to select K neighborhoods $\{N_{P(h)}\}_{h=1}^{K}$.

Assign the data points $\left\{X_h^{(0)} \leftarrow N_{P(h)}\right\}_{h=1}^{K}$

Initialize $\left\{\mu_h^{(0)}\right\}_{h=1}^{K}$

Else

$\left\{X_h^{(0)} \leftarrow N_h\right\}_{h=1}^{\lambda}$

Initialize remaining clusters at random

Initialize $\left\{\mu_h^{(0)}\right\}_{h=1}^{K}$

1.2. Update metrics A_h for all clusters $\left\{X_h\right\}_{h=1}^{K}$ (Eq. (6)).

2. Initialization of maximally separated points $\left(x_h^{'}, x_h^{''}\right)$ with respect to each A_h.

3. Repeat until convergence

3.1. For each $x_i \in X$

Randomly select $\overline{M} \in \left\{(x_i, x_j) \in M\right\}$, $\left|\overline{M}\right| = cts_{size}$ $\overline{C} \in \left\{(x_i, x_j) \in C\right\}$, $\left|\overline{C}\right| = cts_{size}$.

$$h^* = \arg\min_h \left(\left\| x_i - \mu_h^{(t)} \right\|_{A_h}^2 - \log\left(\det\left(A_h\right)\right) + \sum_{(x_i,x_j)\in\overline{M}} w_{ij} f_M\left(x_i, x_j\right) 1\left[h \neq l_j\right] + \sum_{(x_i,x_j)\in\overline{C}} \overline{w_{ij}} f_C\left(x_i, x_j\right) 1\left[h = l_j\right] \right)$$

Assign x_i to $X_{h^*}^{t+1}$

3.2. For each cluster X_h, $\left\{ \mu_h^{(t+1)} \leftarrow \frac{1}{\left|X_h^{t+1}\right|} \sum_{x \in X_h^{t+1}} x \right\}$

3.3. Update_metrics A_h for all clusters $\left\{X_h\right\}_{h=1}^{K}$ (Eq. (6))

3.4. $t \leftarrow t+1$

Algorithm 2. eMPCK-Means

Algorithm 2 shows the proposed eMPCK-Means with the above modifications to MPCK-Means. Step 1 decides the starting *K* centroids (means) for the clusters through the use of initial user feedback. For the specific case of the user flagging calls as SPIT or non-SPIT, *K*=2.

Step 2 initializes the maximally separated points estimation. Step 3.1 performs the cluster assignment. Step 3.2 updates the mean. Note that the mean can be updated in constant time by keeping the sum of the data points and performing an addition/subtraction when a data point is associated with/unassociated from a cluster. Step 3.3 updates the matrix A_h for each cluster *h* based on calculating the covariance matrix on the latest clustering results as used in Mahalanobis distance [28] and also factors in the training data given in the must-link set *M* and cannot-link set *C* (Eq. (6)). The goal of this process is to pick the A_h such that the objective function (Eq. (2)) is minimized for the cluster assignment done in the current iteration of Step 3. From a high-level point of view, this process will result in A_h that puts higher weights on those features which are consistent among data points in the same cluster and lower weights on those that are less consistent.

Overall, eMPCK-Means is shown to be of O(*N*) complexity within each iteration leading to convergence and empirically, the algorithm needs a small number of iterations. Along with the time advantage, the clustering quality and detection accuracy are also improved beyond the original MPCK-Means algorithm.

3.6 pMPCK-Means (Progressive MPCK-Means)

Both MPCK-Means and eMPCK-Means assume the data points are available in a batch, and they are directly suited for the Mode B (batch mode) detection (Sec. 3.3). To support the Mode A per-call or early detection, we create a variant called pMPCK-Means. The pseudo code is given as Algorithm 3. The idea here is that when a new call comes in, pMPCK-Means performs only the cluster assignment step and only for the new data point. Some features in the data point like "duration of dialog", "# of ACKs", "# of BYEs", and "# of xxx response messages" will not be available till the end of the call, while the features like "From URI", "To URI", and "Time from the last call by the same caller" are available at the beginning of the phone call and are used in pMPCK-Means. For the features that are not available, pMPCK-Means fills the data point x_i with the mean values from the cluster to which this point's distance is being computed. This is implicitly carried out in Step 4 of Algorithm 3.

In pMPCK-Means, the update metrics operation only occurs occasionally when the cluster means have changed significantly (exceeding a given threshold $d_{threshold}$). Estimating the mean is a O(1) operation for the addition of each data point. This amortizes over many calls the cost of A_h computation and the cost of re-clustering all existing data points. However, a cost has to be paid in advance, which is that we require reasonably sized cluster(s) to be grown on the initial data points through eMPCK-Means. The reason is that we want the initial A_h matrix to be as accurate as possible and the threshold for the size is denoted as $t_{threshold}$ in Algorithm 3.

Algorithm: pMPCK-Means

Input: A new data point x_t. , Disjoint K-partitioning $\left\{X_h^{(t-1)}\right\}_{h=1}^{K}$ of $X^{(t-1)} = \left\{x_1, x_2, .., x_{t-1}\right\}$.

Output: the cluster association l_t for the point x_t.

Disjoint K-partitioning $\left\{X_h^{(t)}\right\}_{h=1}^{K}$ of $X^{(t)} = \left\{x_1, x_2, .., x_{t-1}, x_t\right\}$.

Internal Variables: $\left\{\widehat{\mu_h}\right\}_{h=1}^{K}$

Method:

1. If $t < t_{threshold}$

$X^{(t)} \leftarrow X^{(t-1)} \cup \left\{x_t\right\}$

$\left\{X_h^{(t)} \leftarrow \varnothing\right\}_{h=1}^{K}$

Return

2. If $\left\{X_h^{(t)} = \varnothing\right\}_{h=1}^{K}$ (all clusters are empty)

$X^{(t)} \leftarrow X^{(t-1)} \cup \left\{x_t\right\}$.

Call eMPCK-Means to generate $\left\{X_h^{(t)}\right\}_{h=1}^{K}$ from $X^{(t)}$.

$\left\{\widehat{\mu_h} \leftarrow \mu_h^{(t)}\right\}_{h=1}^{K}$

Return

3. Randomly select $\overline{M} \in \left\{(x_i, x_j) \in M\right\}$, $\left|\overline{M}\right| = cts_{size}$ $\overline{C} \in \left\{(x_i, x_j) \in C\right\}$, $\left|\overline{C}\right| = cts_{size}$.

4. $$h^* = \arg\min_h \left(\left\| x_i - \mu_h^{(t)} \right\|_{A_h}^2 - \log\left(\det\left(A_h\right)\right) + \sum_{(x_i,x_j)\in\overline{M}} w_{ij} f_M\left(x_i, x_j\right) 1\left[h \neq l_j\right] + \sum_{(x_i,x_j)\in\overline{C}} \overline{w_{ij}} f_C\left(x_i, x_j\right) 1\left[h = l_j\right] \right)$$

5. $\left\{X_h^{(t)} \leftarrow X_h^{(t-1)}\right\}_{h=1}^{K}$

6. $X_{h^*}^{(t)} \leftarrow X_{h^*}^{(t)} \cup \{x_t\}$

7. If $\left\|\widehat{\mu_{h^*}} - \mu_{h^*}\right\|_{A_{h^*}}^2 / \left\|x'_{h^*} - x''_{h^*}\right\|_{A_{h^*}}^2 > d_{\text{threshold}}$

Call eMPCK-Means with initial centroids $\left\{\mu_h^{(t)}\right\}_{h=1}^{K}$ to generate $\left\{X_h^{(t)}\right\}_{h=1}^{K}$ on $X^{(t)}$.

$\left\{\widehat{\mu_h} \leftarrow \mu_h^{(t)}\right\}_{h=1}^{K}$.

Algorithm 3. pMPCK-Means

3.7 Multi-Class eMPCK clustering

We create a variant of eMPCK in which the initial clusters are split into sub-clusters based on the call types "calls going to voice mail", "calls terminated immediately after the call is established", and "the remaining calls". These three types exhibit different patterns in the non-silence call duration ratio (feature 17, Sec. 3.4.2). The sub-clusters are formed for both SPIT and non-SPIT calls. This is an attempt to guide the clustering process through expert knowledge. The user feedback however is only able to differentiate between SPIT and non-SPIT calls, and not place a call into a sub-cluster.

4. Experiments and Results

4.1 Testbed

We set up a two-domain testbed with a topology similar to Figure 2, one of the domains being protected by our detection technique. We use Asterisk [29] as the VoIP proxy servers and use MjSip [30] for the phone clients. Each domain has 90 phones acting as non-spitters and 6 phones acting as spitters. We use the Poisson [28] distribution to model call arrival times and the Exponential distribution to model call durations.

The generation of call traces was done by only one of the co-authors without providing any information about the mix of Non-SPIT and SPIT calls to the rest of the team. This was done on purpose so that the team working on the detection system does not have any prior knowledge of the call mix. Ideally we would have liked to perform the evaluation on third-party call traces. However, at the time of writing, no such call trace is publicly available. Setting up a VoIP system within our university is also not a solution, since the corresponding call trace is unlikely to have any significant number of SPIT calls.

4.2 Summary of call trace dataset

We collected four call traces from our testbed with varying call characteristics as follows (*call trace name*, *Non-SPIT Call length average*, *Non-SPIT Call inter-arrival time average*, *SPIT Call length average*, *SPIT call inter-arrival time average*, *Number of SPIT calls in trace*, *Number of non-SPIT calls in trace*): *(v4, 5, 30, 1, 2, 212, 171), (v5, 5, 10, 1, 10, 45, 338), (v6, 5, 30, 1, 10, 94, 289), (v7, 5, 30, 5, 10, 81, 302).* The time unit is minute. In terms of similarity between SPIT and non-SPIT calls, in decreasing order, the call traces are v5, v7, v6, and v4.

There are other characteristics which are shared by the four call traces. Examples include a 60% chance of a call being hung up by the caller for a non-SPIT call and a 10% chance of being hung up by the caller (spitter) for a SPIT call. The media streams for a SPIT call are dominated by the spitter while for a non-SPIT call, the non-silence duration on the caller and the callee media streams are about the same on average.

Other experimental parameter settings are: at most 15 must-link and 15 cannot-link constraints are used in our algorithms. The pMPCK-Means algorithm queues 100 data points initially and runs eMPCK-Means before commencing incremental operation for subsequent points. The convergence criterion is that the clustering does not change from the previous iteration or a previously seen clustering is revisited. Each data point in the experiment is based on the average from 50 runs with the same parameter settings.

4.3 Effect of proportion of user feedback

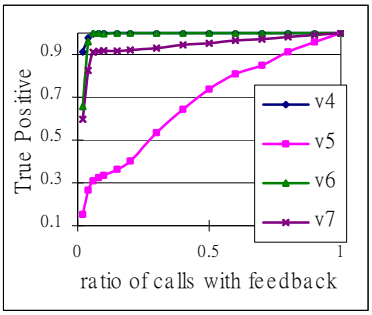


Figure 4. Compare eMPCK True Positive Rate across call traces 4,5,6, and 7

In this experiment, we evaluate the effect of the proportion of calls that come with user feedback. We assume the same ratio for both SPIT and non-SPIT calls. We assume the feedback is perfectly accurate.

Figure 5 shows the clustering quality with respect to four different algorithms proposed on call trace 4 in terms of the F-Measure [6].

The F-Measure is defined as follows:

Precision = (# pairs correctly predicted in same cluster)/(total # pairs predicted in same cluster)

Recall = (# pairs correctly predicted in same cluster)/(total # pairs in same cluster)

F-Measure = (2 × Precision × Recall)/(Precision + Recall) (7)

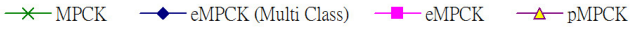
A larger F-Measure value means better quality clustering. From Sec. 4.2, we know that call trace 4 exhibits a very clear distinction between SPIT and non-SPIT calls in terms of call duration and call inter-arrival time. This makes eMPCK perform well with user feedback ratio as low as 0.1. The original MPCK-Means achieves the same level but with a higher user feedback ratio of 0.2. The improved result of eMPCK is due to the pre-metrics update (Sec. 3.5.4), which creates a more accurate weight matrix A based on user feedback, prior to iterating over the data points. The F-Measure from eMPCK Multi Class drops with increasing user feedback ratio because we break the cluster into sub-clusters based on the call types. As a result, eMPCK Multi Class will put different types of SPIT and non-SPIT calls into different sub-clusters. Both will hurt the F-Measure since by definition of F-Measure, these calls should be clustered into the same cluster. This negative effect grows stronger as the user feedback ratio increases.

Figure 6 and Figure 7 show the true positive and false positive rates of SPIT detection on call trace v4. What we can see here is that eMPCK Multi Class actually performs well despite the poor F-Measure. eMPCK Multi Class performs worse than eMPCK at low user feedback ratio because breaking the initial cluster into sub-clusters reduces the number of call data points with feedback in each sub-cluster. This results in poor clustering and hence low

detection accuracy. Compared to eMPCK, MPCK's detection accuracy lags behind due to the lack of pre-metrics updating. pMPCK performs rather poorly even with call trace v4. However, it is still in the usable range (e.g. 0.63 True Positive with a user feedback ratio of 0.2). pMPCK's poor performance is due to the limited features available before the media stream is established.

Due to space constraints, we show only the True Positive curves for call traces v5, v6, and v7 in Figure 8, Figure 9, and Figure 10 respectively. All the algorithms perform worse with call trace v5 due to same inter-arrival time of SPIT and non-SPIT calls. This makes the time since last call from the same caller and call frequency (features 9 and 16 in Sec. 3.4.2) much less useful. Another factor is the number of SPIT calls in the call trace is decreased to 45 (compared to 212 in v4) which further hampers the clustering quality and detection accuracy. Figure 4 summarizes the True Positive rates from eMPCK across the four call traces. This basically corresponds to how salient the differences between SPIT calls and non-SPIT calls in the call traces are. In order, the easiest one is v4, followed closely by v6, and then v7. The hardest is v5. One thing to note is that in v5, SPIT calls are almost non-distinguishable from short-duration non-SPIT calls.

We show error-bar (± 1 s.t.d.) for eMPCK in Figure 5. They are omitted in the rest of the figures for presentation clarity. The general trend is that the errors diminish with increasing ratio of user feedback. We observe less than ± 5% error across the experiments on call traces 4,6,and 7 when user ratio is set beyond 0.1. For call trace 5, the error is higher (up to ± 25% at 0.1 ratio). This is due to the fact that trace 5 is the hardest for detection as mentioned in previous paragraph.



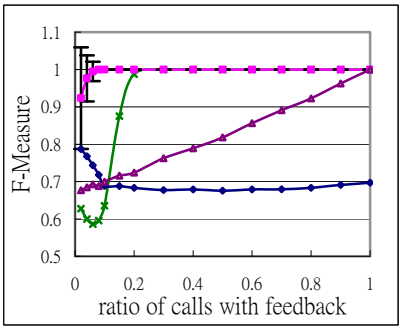


Figure 5. Call trace v4 / F-Measure with all algorithms

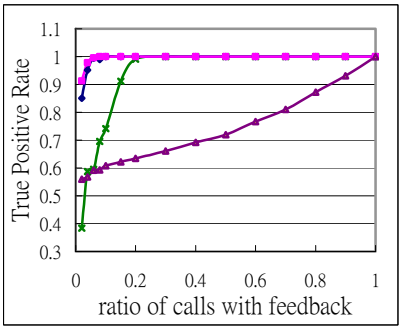


Figure 6. Call trace v4 / True Positive rate

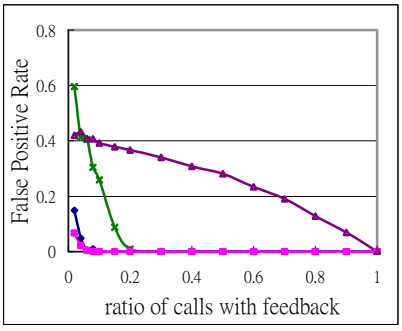


Figure 7. Call trace 4 / False Positive rate

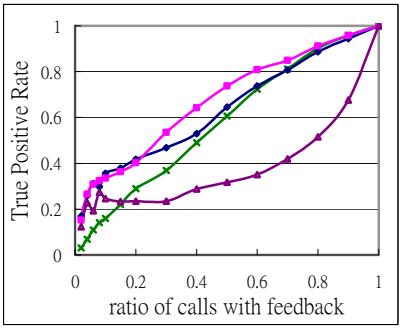


Figure 8. Call trace 5 / True Positive Rate

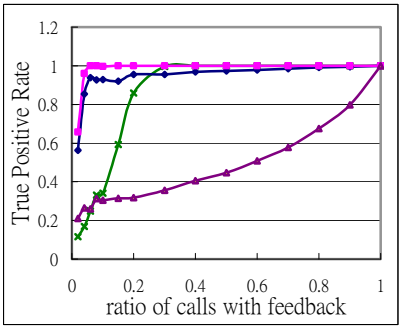


Figure 9. Call trace 6 / True Positive Rate

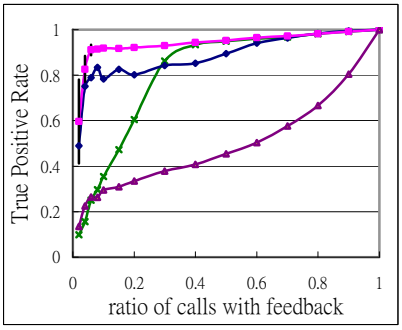


Figure 10. Call trace 7 / True Positive Rate

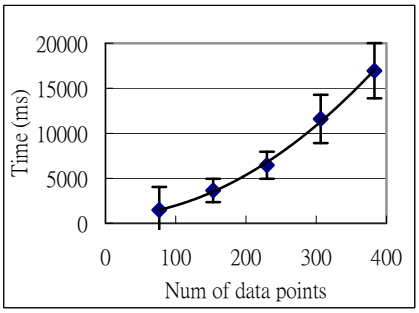


Figure 11. MPCK Running time

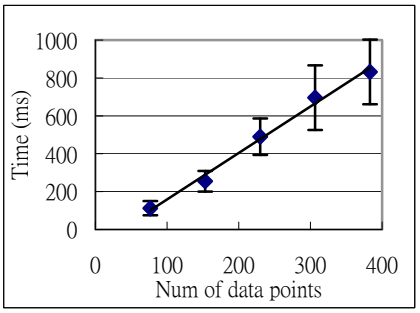


Figure 12. eMPCK Running time

	MPCK	eMPCK
v4	6.94	3.98
v5	7.80	7.83
v6	7.81	5.38
v7	6.94	4.7
Average	7.37	5.47

Table 1. Number of iterations to convergence

4.4 Scalability of execution time

In this experiment we compare the running times of MPCK and eMPCK by varying the number of call data points. Call trace v7 is used for this experiment. For MPCK, we apply exact optimizations which do not cause loss of accuracy. For example, the maximally separated points evaluation is re-executed only when the A matrix gets changed. The results are based on code compiled with MS VC++ 8.0 with default optimization level running on Windows XP, Intel E6400 2.13 GHz CPU.

As Figure 11 and Figure 12 shows, MPCK exhibits non-linear growth in the running time as the number of call data points increases and is therefore non-scalable. eMPCK, on the other hand, exhibits a linear growth in the running time. The error bars are based on ± s.t.d.. Also, MPCK takes significantly longer time to run compared with eMPCK with the same number of input data points. Looking at the number of iterations that each algorithm takes to converge (Table 1), eMPCK fares better. The running time advantage of eMPCK comes from the lower number of iterations as well as the lower running time of each iteration. The lower number of iterations is explained by eMPCK's initial update of A_h's on the starting clusters. For call trace v5, the similarity in SPIT and non-SPIT calls renders the A_h initialization ineffective and the number of iterations is roughly equal for both algorithms.

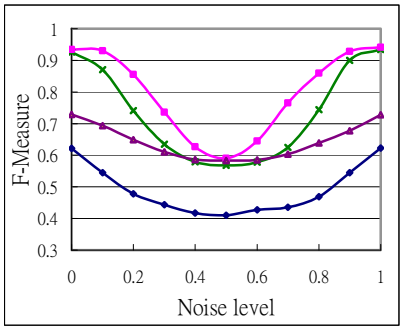


Figure 13. eMPCK / F-Measure vs. Noise

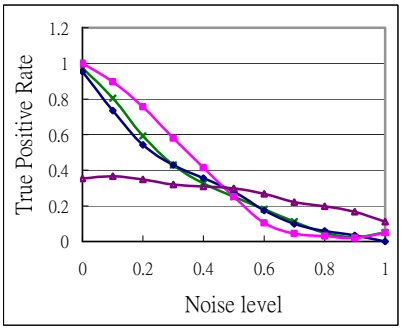


Figure 14. eMPCK / True Positive vs. Noise

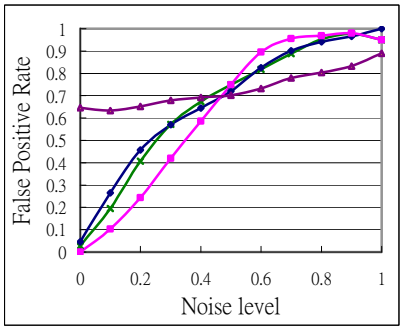


Figure 15. eMPCK /False Positive vs. Noise

4.5 Effect of noise in user feedback

In this experiment, we perform an evaluation of the different algorithms with various noise levels in the user feedback. When we say the noise level is *c*, it means that a fraction *c* of the user feedback is false, i.e., a SPIT call is reported as non-SPIT and vice-versa. We show the result with call trace 6 for this experiment. The user feedback ratio is fixed at 0.3. Figure 13 shows the effect on the F-Measure, where the curves are symmetric around 0.5 noise level. This is understandable since F-Measure cares only about the clustering quality and not the absolute SPIT/non-SPIT cluster association. Figure 14 shows the true positive rate decreases as the noise level increases. Observing the false positive rates in Figure 15, we conclude that pMPCK is completely unusable through the whole noise level range while the other algorithms are usable at low noise levels. We conclude that pMPCK is usable only for a high proportion of accurate user feedback. Beyond noise level 0.5 eMPCK performance drops below that of MPCK due to our design of the detection predicate (Sec. 3.4.6), namely, considering the cluster that contains more calls marked by the user as SPIT than non-SPIT, to be the SPIT cluster. With noise level above 0.5, the user feedback is wrong more often than right and the negative effect is more pronounced in eMPCK than MPCK, since it did a "better job" of clustering on the user feedback than MPCK. As an example of a usable operating point, consider that at noise levels 0.2 or below, eMPCK has both true positive and true negative above 0.8.

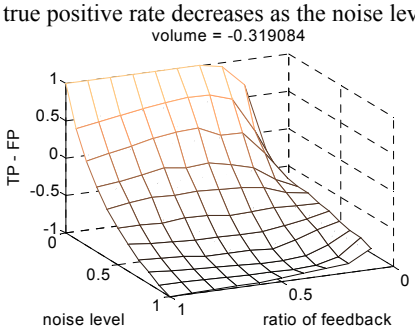


Figure 16. MPCK (True Positive – False Positive) / call trace v6

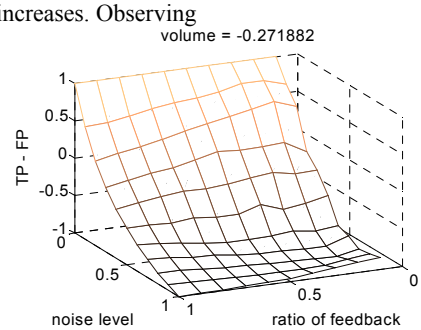


Figure 17. eMPCK (True Positive – False Positive) / call trace 6

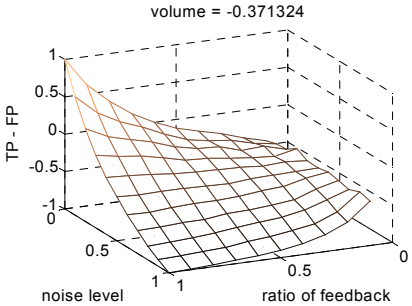


Figure 18. pMPCK (True Positive – False Positive) / call trace 6

4.6 Evaluation with noise and feedback ratio

$$Volume = \int_{n=0}^{1} \int_{f=0.1}^{1} (TP - FP) \bullet df \bullet dn \quad (8)$$

n : noise level, f :feedback ratio

TP-FP Volume	v4	v5	v6	v7	avg.
MPCK	0.048	-0.595	-0.319	-0.388	-0.314
eMPCK (Multi Class)	0.068	-0.590	-0.330	-0.402	-0.314
eMPCK	0.042	-0.577	-0.272	-0.340	-0.287
pMPCK	0.015	-0.596	-0.371	-0.411	-0.341

Table 2. Summary of TP-FP volume comparisons

Here we perform an evaluation of all four proposed algorithms with respect to the four call traces. Our evaluation methodology considers the combined effect of proportion of user feedback and the noise level and the results are shown in Figure 16, Figure 17, and Figure 18. In the 3D plot, the Z-axis corresponds to (TP-FP), the difference between True Positive rate and False Positive rate, with respect to each pair of feedback ratio and noise level. Intuitively, if (TP-FP) is greater than zero, it means the detection gives more correct results than incorrect results and can be regarded as a valid operating point where the detection is useful. Due to page length limitation, we show the 3D plots only for call trace 6. A general trend we can see in the 3D plots is that when fixing the noise level, the (TP-FP) value climbs to a peak and then goes down when varying the feedback ratio from 0 to 1. There is no sharp breakdown of performance for any of the algorithms. If the user feedback is accurate, then even with low ratio of user feedback, the performance is good for MPCK and eMPCK. The performance of pMPCK on the other hand is acceptable only close to the extreme region of almost perfect user feedback for almost all calls. Expectedly, at the extreme noise level of 0, the peaks are at the location with feedback ratio 1; at the extreme case of noise level 1, the peaks are at feedback ratio 0.

To give an overall quantification of the detection quality, we define the volume metric based on the integral (Eq. (8)). In the ideal case where (TP-FP) is maintained at 1 through the entire range of noise levels and feedback ratio values, the volume will be 0.9. Table 2 shows the volume for each combination of algorithm and call trace. Call trace v5 gives the lowest volume corresponding to the worst performance for all algorithms. Averaged over the entire range, we see that eMPCK performs best followed by eMPCK (Multi Class), MPCK, and pMPCK.

5. CONCLUSION

In this paper, we proposed a new approach to detect SPIT calls in a VoIP environment. We map each phone call into a data point based on an extendable set of call features, derived from the signaling as well as the media protocols. This converts the problem of SPIT detection into a data classification problem, where a classic solution is the use of clustering. We apply semi-supervised clustering, which allows for the optional use of user feedback for more accurate classification. This corresponds to users' flagging some calls as SPIT and others as legitimate.

A challenge we encounter is that the MPCK-Means semi-supervised clustering algorithm is not scalable with the number of data points. Furthermore, for our specific problem on classifying VoIP calls, it requires at least 30% of calls to have user feedback to achieve high (> 90%) detection true positive rates. This is likely too onerous to the end users. Therefore, we create a new algorithm called eMPCK-Means which provides empirically linear time performance – speeding up the performance of MPCK-Means fifteen fold. It achieves this by replacing the time-consuming parts in the MPCK-Means algorithm with domain-specific approximations. We introduce a pre-metrics-update step, which contributes to high (> 90%) detection true positive rates with less than 10% user feedback data points for three of the four call traces used here. We found that it is difficult to attain high detection accuracy based only on features available in the call establishment phase, which would enable a SPIT call to be dropped without the user needing to answer the call. This algorithm pMPCK performs well only with accurate user feedback for a majority of calls.

One possible improvement is to include the trust/reputation of callers as a feature in the clustering. However, as mentioned earlier in Sec. 2, we would have to address the drawbacks of classical reputation systems. We are also interested in further features that can be extracted from media traffic that can aid in the classification. This brings in the question of feasibility, considering the load that such processing will place on the client-side detectors, especially considering that some hard phones may be quite limited in their processing capabilities. Implicitly we have assumed that noise in user feedback is due to honest mistakes, not malicious users trying to steer the clustering in wrong directions. How should the system protect itself when the assumption is no longer true? Could it be possible to identify such users and downgrade their feedback for the clustering process?

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